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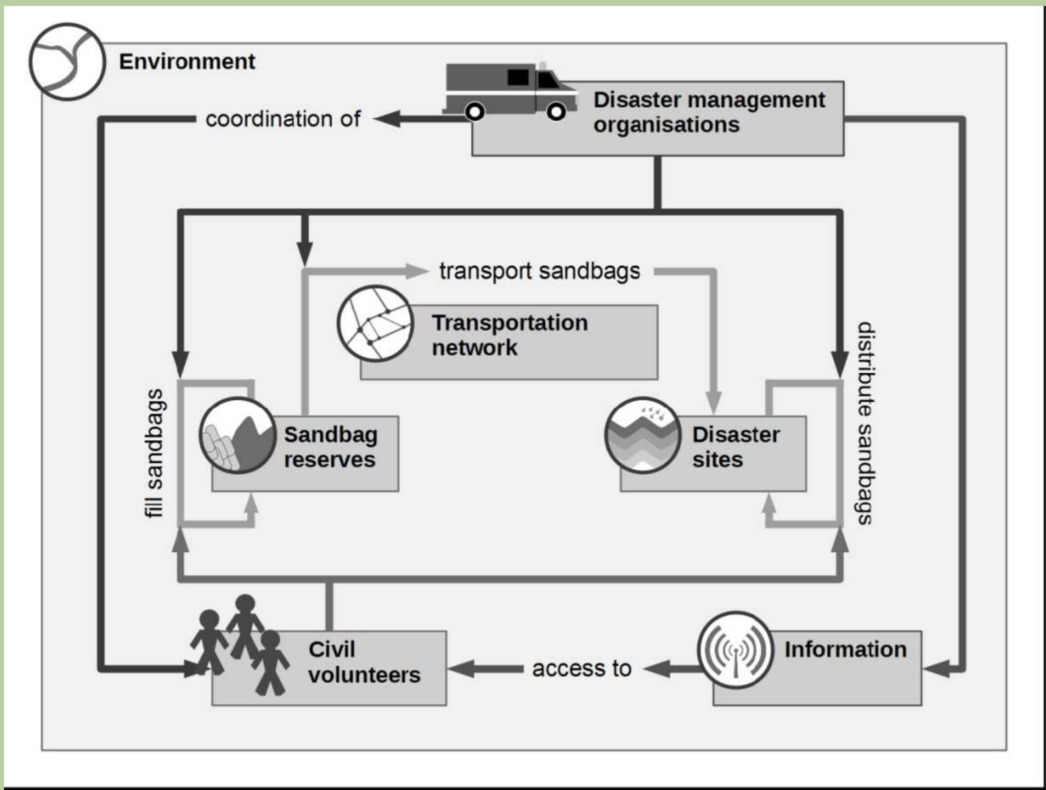
Developing agent-based models for community resilience

Connecting indicators and interventions

Deliverable 4.4/4.5



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Short Description: This report is the documentation of the emBRACE task 4.5 on simulating community resilience using ABM, which was linked to the following two deliverables: D4.4: Report on the development of agent based models and their application in case studies D4.5: Report on assessment of indicators of resilience using historically informed ABM

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Partner/s contributed: University of York, UFZ, University of Reading
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About emBRACE

The primary aim of the emBRACE project is to build resilience to disasters amongst communities in Europe. To achieve this, it is vital to merge research knowledge, networking and practices as a prerequisite for more coherent scientific approaches. This we will do in the most collaborative way possible.

Specific Objectives

- ⇨ Identify the key dimensions of resilience across a range of disciplines and domains
- ⇨ Develop indicators and indicator systems to measure resilience concerning natural disaster events
- ⇨ Model societal resilience through simulation experiments
- ⇨ Provide a general conceptual framework of resilience, tested and grounded in cross-cultural contexts
- ⇨ Build networks and share knowledge across a range of stakeholders
- ⇨ Tailor communication products and project outputs and outcomes effectively to multiple collaborators, stakeholders and user groups

The emBRACE Methodology

The emBRACE project is methodologically rich and draws on partner expertise across the research methods spectrum. It will apply these methods across scales from the very local to the European.

emBRACE is structured around 9 Work Packages. WP1 will be a systematic evaluation of literature on resilience in the context of natural hazards and disasters. WP2 will develop a conceptual framework. WP3 comprises a disaster data review and needs assessment. WP4 will model societal resilience. WP5 will contextualise resilience using a series of Case studies (floods, heat waves, earthquakes and alpine hazards) across Europe (Czech Republic, Germany, Italy, Poland, Switzerland, Turkey and UK). WP6 will refine the framework: bridging theory, methods and practice. WP7 will exchange knowledge amongst a range of stakeholders. WP8 Policy and practice communication outputs to improve resilience-building in European societies.

Partners

- ⇨ Université catholique de Louvain (UCL) - **Belgium**
- ⇨ University of Northumbria at Newcastle (UoN) - **UK**
- ⇨ King's College London (KCL) - **UK**
- ⇨ United Nations University Institute for Environment and Human Security (UNU), **Bonn**
- ⇨ Accademia Europea per la Ricerca Applicata ed il Per-fezionamento Professionale Bolzano (EURAC) - **Italy**
- ⇨ Helmholtz-Zentrum Fuer Umweltforschung GMBH - UFZ (UFZ) - **Germany**
- ⇨ University of York (SEI-Y) - **UK**
- ⇨ Stockholm Environment Institute - Oxford Office Limited (SEI-O) - **UK**
- ⇨ Swiss Federal Institute for Forest, Snow and Landscape Research - WSL (WSL) - **Switzerland**
- ⇨ Middle East Technical University - Ankara (METU) – **Turkey**
- ⇨ University of Reading (UoR) - **UK**

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1. Introduction

This deliverable aims at addressing one of the overall emBRACE objectives (see page ii): that is to model societal resilience through simulation experiments in order to contribute to an understanding of community resilience from a methodological point of view. We must consider this position as a starting point and as an introductory context to this deliverable, before looking at development of modelling and the many different approaches available. Task 4.5 concerns computer simulation models (agent-based models), and its focus of enquiry is on resilience at the municipality, organisation, or city level. Simulation is just one of a number of modelling approaches taken in the emBRACE project. Work package 4 concerns the development and improvement of methods for modelling resilience and links work package 5 assessments of these methods through the empirical application within five case studies.

Considering uses of modelling, several concepts are important to keep in mind. Firstly, modelling helps the investigator to explore the complexity of the situation where environment is coupled with the social system (and sub-systems to be considered, e.g. geography, community system, policy and institutional systems), and both the modelling process and model outputs can help to clarify and to communicate that understanding. Disaster management situations are often described as complex systems given their characteristic unpredictability, uncertainty, sensitivity to initial conditions, interconnectedness. Examples in the literature will be given below. This exploration helps to generate new knowledge; modelling is particularly useful for looking, experimentally, at possible future evolutions of the situation, using simulations.

Secondly, given that considerable complexity is represented, there are further questions about dynamics of complexity which are particularly relevant for us in emBRACE: these are to do with the actual dynamics of social complexity (*e.g. cf.* McLennan 2003); the interplay between social and natural sciences and engineering involved in DRR planning and responses (*e.g. cf.* Donaldson et al 2010); and the complexity of our responses to these complex situations (cf. Ramalingam et al 2008). These questions address untangling the factors important for how resilience changes over time. For example, in terms of social resilience: why is one community different from another and how do these differences arise and play out. In terms of individual resilience: how do people adapt differently to different types of interventions, in the long and the short run: and what is the relationship between individual [agent/actor] resilience and community-level resilience. The point is to use simulations and simulation data as an aid (where real data is often scarce), in combination with other methods, to help both researchers and practitioners, and community members themselves, in understanding dynamics, correlations among different factors, and possible causal mechanisms.

Thirdly, it offers an opportunity for integration of different types of knowledge (i.e. technical, traditional, local) and with the participation of different stakeholders, reality-checking and elicitation of preferences. In the best case it allows different actors to "play" with some representations of community resilience, on the basis of including different knowledge frames, to generate shared understandings and co-learning.

his deliverable describes the progress made towards the aim of modelling societal resilience through simulation experiments, and it should be read alongside framework document (in emBRACE Deliverable 6.6 (Jülich, Kruse and Björnsen Gurung 2014) and subsequent developments of the emBRACE framework – see Fig 1.1 below), for understanding the overall meta-model of emBRACE. However, the ABM work also links to the framework through case studies. Thus, actual realities of each case study's social and civil *Actions*; experience and *Learning*; and natural and social-political *Resources & Capacities* can be explored within the context existing there, allowing case-study-specific explorations to be carried out within an understanding provided by the generic framework.

However, the ABM method was not used heavily in the emBRACE project. The case study team working on Floods in Central Europe used the method. The case study team working on earthquakes in Turkey commented on another of the models which was found relevant – although data were not available such that direct application could be made. Therefore we report on two ABMs, one looking at disaster response in Germany, and another looking at disaster preparation in a more general way but connected with some aspects in the Turkish case study. Other cases considered using ABM: e.g. the London heatwaves case (see Grimmond et al 2014) and the Alpine multi-hazard study (Pedoth et al 2015). These considerations have been integrated into an outlook section in part five of this deliverable.

Fig. 1.1: the final iteration of the emBRACE framework

Section three details the ABM cases and combines the two parts: one on 'historically informed modelling' (was emBRACE Del.4.5) and one on 'modelling intervention scenarios' (was emBRACE Del.4.4) into one deliverable. A variety of methods have been used in the emBRACE project and these – and the potential for their close relation to ABM – are further detailed in section four. Section five concludes.

2. Background to the use of ABMs

This section updates the literature reviews of Del. 1.1 and Del. 1.3 (Birkmann et al 2012) from earlier in the project, concerning methods for modelling resilience. We begin with a brief introduction to the method.

Agent-based modelling concentrates on describing the social system at the micro-level of the actors within it, and nowadays this is usually done using a computer model (program). In this system, an agent is an autonomous piece of program code representing an actor in a social system. With great design flexibility, ABM can be used to model many or multiple types of agency at different levels of action. The agent design templates are used to create many 'instances' of these actor-representations, and thereby populate the model (hence, ABMs are sometimes also known as multi-agent models).

ABM is also noted for being a highly flexible method, which does not depend on an *a priori* set of given techniques or assumptions, and without particular attachment to any theoretical approach. In this respect, ABM may lend itself to being more directly informed from observation and evidence – although the cost and difficulty to collect sufficient data continually presents a barrier. Usually the rules of behaviour of agents are informed, empirically, from a combination of field studies, participant methods (e.g. games, co-construction workshops), and case studies, or sometimes from stylised facts (*cf* also the emBRACE deliverable on social network mapping (Matin et al 2015), which also discusses data gathering issues and also the use of stylized facts – see particularly section on complex dynamic social networks).

There is also an important role for theory in ABM. In this respect, it can be argued that there is a lack of appropriate social theory that may be linked to social simulation modelling (This is, for example, very unlike social network mapping). Central though the concerns of sociology are; it is noticeable the deficit of theory on how humans actually interact which can be used readily in agent-based computer simulation; moreover much is still to be learnt about social factors in actor decision making. Decision networks (a.k.a. influence diagrams) sometimes used in psychology are often simplified enough representations of social realities to be useful in programming an agent's behaviour. Nonetheless, this is a longstanding area of interest for people using ABM, which does presuppose rich social interaction **. In this respect, much ABM work could be seen potentially as an opportunity for developing and expanding this theory, as well as having much to contribute to the discussion on the possible links between micro and macro.

Another of the major continuing themes of ABM (as with social network analysis: Hanneman & Riddle, 2005) is the way in which individual actors "make" larger social structures through their patterns of interaction while, at the same time, “society” - and its institutions - shape the choices made by the individuals who are embedded within structures.

The design of agent attributes and rules step involves a clarification and formalisation of knowledge about the target social system, and it also involves an abstraction step as we cannot (and nor would we want to) attempt to capture everything. Here Zeitlyn and Just’s “Merological Anthropology” (2014) is perfectly designed as a theoretical framing. Zeitlyn (2009) describes merological anthropology as “partial” (in the sense of describing part of the system well but also from a particular standpoint). We can have good confidence in that bit of the system which we do know, and structuring our understanding – e.g. through the application of an ABM – allows us to organise, reduce, and select (op.cit: 211) what ‘facts’ we have confidence in.

Having described the micro-foundational aspects, the simulation is used to explore consequences the model design by observing the aggregate (macro) outputs of the model. Batches of simulations are run as experiments to test different assumptions, different parameter choices, different initial conditions and scenarios etc.

Validation is done by testing 'reality of assumptions' with stakeholders. Participation is designed as an iterative process to help clarify stakeholders' understandings, to improve the accuracy with which their knowledge is represented in the model, and to improve a model's relevance.

ABM helps in understanding relationships and thus possible causal mechanisms in complex systems, by generating them 'from the bottom-up'. In other words, ABM helps with the explanation of certain complex phenomena, through development of theory and simulation experiments carried out. It is useful for exploring consequences of sets of assumptions (model rules) that interact through strong dependencies and trigger feedbacks.

It can be useful to make a first, crude, distinction between foundational and empirical models. Moss (2001) defines foundational agent-based social simulation (ABSS) as research concerned with formulation and verification of social theory and design of agent architectures, and representational ABSS as the use of multi-agent systems

(MAS[1]) to describe observed social systems, arguing that there are very few examples of well-validated representational models. Boero and Squazzoni (2005) proposed three categories of agent-based model: 'theoretical abstractions', 'typifications' and 'case-based models. More recently Schlüter et al. (2012) and others have written about this dichotomy. One of the dimensions proposed by the Schlüter et al. MORE framework is the modelling level of abstraction – from generic to context- based, which corresponds to orientation either towards foundational theory or towards case study empiricism.

Most authors agree, however, the boundary between the two strands of research is not always so clear-cut. In this deliverable we will report on development of different types of models – a more abstract one in the case of disaster preparedness and a more case-focussed one in the case of disaster response. We discuss lessons learned in terms of development of the methodology and an outlook on further uptake.

In fact, choosing an ABM approach is only relevant in the case where one is trying to explore the consequences of dense interaction among actors in a social system (bringing on board the concepts of social networks, dynamics of norms, imitation, social learning, social influence, power, social coordination and control). ABM could work well as part of a suite of methods used to explore and understand complex social systems (Taylor et al 2014: 261): further, ABM can be used with other modelling methods such as systems models and unified modelling language (Forrester et al 2014) but also, potentially, with numerical models such as those routinely used by geologists, hydrologists, seismologists, volcanologists and other technical disaster experts.

In recent years, many researchers have developed ABMs in the context of environmental resources, ecological dynamics, and development or adaptation processes under environmental change.

We now turn to discussion of this growing literature, moving from an interpretation of the history of development of different trends in resilience modelling research, to

[1] The generic term Multi-Agent System (MAS) applies to all such distributed systems and applications, whereas if we are concerned only with models, ABMs, and still more specific - social models are also referred to as Agent-Based Social Simulations (ABSS).

some recent examples of state of the art in resilience modelling. This section discusses differences and commonalities among modelling approaches looking at climate adaptation and resilience. This is followed by a discussion of dynamic simulation modelling, looking in more detail at particular techniques and referring to some good examples of their application on research in community resilience. In the text box below, links to further resources are also provided.

A selection of introductory articles for further reading:

May 2007 (Issue 2603 pgs.) New Scientist entitled: Interview: Can we model the real world? (An interview with JOSHUA M.EPSTEIN)

Simulation: an emergent perspective (by Nigel Gilbert)

Nigel Gilbert and Klaus G. Troitzsch (2005), Simulation for the Social Scientist,

Nigel Gilbert (2004), Agent-based social simulation: dealing with complexity

2.1. History of development and use in resilience research

Vulnerability and resilience modelling includes a diverse set of approaches including conceptual modelling, statistical modelling and dynamical modelling. Most of the attention has been on the latter. The predictive ability of statistical models depends on the availability of adequate data. Parsimonious statistical models can, in general, provide clarity and better fit to historical data. However, the need to consider multiple drivers of vulnerability and the difficulty of obtaining historical data for all relevant covariates has usually precluded the use of statistical modelling. Dynamical models instead explicitly model the key equations or relationships among model variables. They can potentially be applied in different contexts to those in which they were developed, and to explore and compare possible future states of a system, i.e. scenario analysis.

Whereas many of the concepts and definitions of vulnerability originate in the field of disaster risk research, the modelling techniques have flowed down from macroeconomics and integrated assessment. These include Integrated Assessment Models (IAMs), system dynamics, and Bayesian networks – and in these types of models, there is often input from expert stakeholders in their design. For example, Bayesian networks (BN) and FCMs both involve conceptual modelling with stakeholders – which may be followed by use of computational methods to investigate sensitivities to changes in the different drivers identified. These techniques often also incorporate climate change scenarios.

Research on the concept of ecological resilience, which originated in the early 70's (Holling 1973), has developed independently of hazards and disaster research, and hence independently of this work on vulnerability. Although more recently authors are pointing out the apparent connections between (social-ecological systems) resilience and adaptation research which aims at understanding how adaptation may reduce vulnerabilities. The differences between vulnerability and resilience concepts has been discussed by Miller et al. (2010). Both resilience and vulnerability approaches are concerned with how systems respond to change. However, each approach considers systems in quite different ways. Nelson et al. (2007) observe that the resilience community tends to prefer a systemic approach, whereas the climate change adaptation and the vulnerability communities tend to take an actor-oriented approach (see McLaughlin and Dietz 2007).

Moreover, resilience research has a strong theoretical basis and mathematical formulation. It focuses on modelling of systems and their interconnections, alternative states and critical ecological thresholds, with biophysical variables (particularly ecological ones) more often than socio-economic ones forming the main aspect of study. In this context, system dynamics modelling is a widely used research method for resilience researchers to understand the overall aggregate picture of system function, including its social-ecological relations, and the dynamics in terms of changes in stocks and flows.

Vulnerability studies, on the other hand, normally consider a unit of analysis such as a human-environment system or a catchment system, or a social group, livelihood, or sector. Modelling approaches consider the ecological, social and biophysical aspects of vulnerability in different contexts such as disaster planning, climate adaptation, poverty alleviation, etc. The mathematical modelling approach can provide a framework relevant to any of these fields (Ionescu et al 2009) and is also relevant for the development of further computational tools. Complex systems models, particularly those taking an actor-oriented approach, are used in vulnerability and adaptation research. Adaptation options and strategies identified during an assessment can be further explored through modelling work.

Miller et al. (2010) argue that the two approaches are potentially complementary, in the sense that actor-based analyses look at the processes of negotiation, decision making, and action, whereas systems-based analyses complement this approach by examining the interaction of social and ecological processes. Furthermore, each of these communities has differentially emphasized either the ecological- biophysical or the social-political dimensions of problems under investigation, i.e. that biophysical variables tend to be the focus within resilience research, and historical and political economic processes in vulnerability research.

2.2. Review of ABM and systems-based simulation studies

Applications of ABM in resilience studies are relatively few. In their review and conceptual framing paper which introduces the MORE framework mentioned above, Schlüter et al. (2012) carried out a systematic review of 29 examples of modelling work in the area of social-ecological systems resilience (they remark that models have received rather little attention in SES resilience research so far) finding that the great majority were aimed at improving understanding and providing decision support. According to their own elaboration of review criteria, they highlighted existing gaps/opportunities such as use of models for integration of knowledge and communication of ideas. They also argued that a plurality of methods, model types and applications would be needed to fulfil necessary tasks for modelling.

Interestingly, it was found that the majority (69%) of the studies used difference and differential equations to formulate the model whereas 24% used rule-based models (including ABM) and 24% state and transition models (including SDM). They also observed that human activities are considered independently from environmental stimuli and independently from any context of social interaction among multiple actors. Modelling tends to focus on development and valuation of management strategies - but not on the responses of individual actors to these strategies – therefore these can be characterised as system-based analyses.

The authors observe the models' “very rudimentary representation of the social system” in models that pertain to human activities and their management; they remark that “the potential of models for resilience thinking and ecosystem stewardship is much larger than what is being used today” (Schlüter et al., 2012). Further, in some technical-based ‘systemic’ models the social is almost relegated to a “static externality” (Karin Frank, pers.comm., emBRACE Project Workshop Leipzig, 6-7 March 2012).

Recently we looked, in addition, specifically for agent-based modelling studies that pertain to social resilience that have been published in the last few years (2009 and after; the date of the Schlüter et al. survey) by doing an identical Web of Science search including the term “agent-based” and additionally widening the search including the more broadly dedicated Journal of Artificial Societies and Social Simulation (JASSS). The former yielded 13 publications and the latter yielded around 4 publications and following review we concluded that little had changed since 2009 as far as concerns the use of ABM.

Search terms used for this review:

WoK: TOPIC: (resilience) AND TOPIC: (agent-based) AND TOPIC: (ecol*) AND TOPIC: (management OR resource OR governance)

JASSS: “resilience” and “agent-based”

As a dedicated journal to social simulation (and strongly oriented to ABM) JASSS is a key outlet for the type of work of interest. Within this one journal the search was widened by dropping the ecol* term.

(Searches carried out in March 2015)

The most relevant of these papers (approx. 8 papers) were reviewed for this report. Generally these studies use the term resilience to describe the macro stability of the models and to discuss the pattern of simulation outcomes. For example, Becu et al (2014) refer to social resilience in terms of stability of the model cultivation system over large spatial and temporal scales, in which different balances are established. The authors show demographic cycles in the simulation run reported. Altaweel et al (2010) model group decision making for implementing measures promoting resilience to social-ecological change, although the underlying model is not based on environmental risk factors (it is based on an artificial neural network model). The outcome indicator of interest is the amount of compliance in a village community, tested over different scenarios. Heckbert (2013) reports an archaeological simulation to study development of settlement patterns and their persistence, measured by five different model indicators (population, trade, ecosystem services, forest condition and soil degradation) mapped across geographical space and over time. The biophysical model introduces disturbance to the system through cyclical variation in rainfall model input, which is calibrated on paleoclimatic records. Although climate perturbations are driving the model they “concurrently contribute to resilience or vulnerability” along with other interconnected variables. Parrott et al. (2012) present 3 examples of regional landscape models, including one social network study (not an ABM) of agricultural system resilience. The social network is mapped from interviews and includes governance actors and farmers, and is connected to a habitat network based on remote sensing spatial data. The authors argue that the model can be used to analyse how perturbations caused by removal of nodes or edges might spread through the networks and affect resilience, both in terms of actors (e.g. funding cuts affecting social capital) and habitats (e.g. communicating information about biodiversity protection).

Spies et al. (2014) outline an approach for understanding complexity in a coupled system with challenges for forest fire management. They argue that “one of the main reasons to develop more comprehensive models [...] is to improve social-ecological resilience and adaptation strategies” and introduce a conceptual model as the basis for an ABM. The idea is to test two different models of decision making in which multiple indicators are used (indicators mentioned include timber production, biodiversity and aesthetics). The intention is to use the model with stakeholders to “facilitate dialogue about increasing adaptation and resilience in this fire-prone landscape” and to test management scenarios.

Polhill et al. (2010) adapted an existing model to a particular application context, showing where evidence, i.e. new findings, suggested specific changes. The context is a particular regional landscape, farm managers and farming service providers, and the interest is the “apparent resilience in land use and land ownership change to various shocks over the past 20 years”. Different shocks are explored through ABM in a later working paper by Filatova and Polhill (2012) (not in Web of Knowledge).

This reading of the ABM literature shows that current models remain vague about how they include, and relate to, the concept of resilience. The question of resilience to what type of change, and what sort of adaptation choices (or risk mitigation strategies) that the model considers, are not addressed explicitly. This under-specification seems important because, on the one hand, it is essential to understand what are the conditions of applicability for each model. On the other hand, however, if multiple sorts of social, economic or ecological changes could be studied simultaneously, this could also inform work on the concept of 'generalised resilience'.

The lack of clarity is apparent particularly where the term resilience is used interchangeably with closely related terms such as viability or sustainability. We also find that most studies do not look at the effect of 'shocks' or exogenous disturbances which are a central concept of the resilience literatures. In the case of most ABM literature, modelled changes seem to be ones driven by quite slow or moderate environmental changes rather than shocks such as sudden policy changes or demographic change in the human system (where changes might be faster). In other words shocks are exclusively related to the environmental system (they may overstep a desirable range for the disturbance regime) rather than the social change (where shocks could include new types of economies or social environments). See Filatova and Polhill (2012) for further discussion.

It is interesting that resilience is studied at the emergent level (as an outcome emerging from the lower-level interactions and decisions) rather than addressing resilience at other levels of agency and decision-making, such as at the household-level, or in local community groups and other organisations.

One notable work is Smith (2014) who uses ABM in understanding environmentally induced migration. The starting point for this paper about development and testing of an ABM is a well-specified conceptual model, but lack of underpinning data, especially about spatial and temporal aspects. The author suggests that data usable for modelling are rare and difficult to collect. The main data source available is 'Rainfalls project' case-study data including a survey in 3 communities. This is used initially to derive a statistical model of migration decisions to help understand what attributes to include in the ABM. Surveys at household level are also used to define 'resilience' of a household to changing rainfall distributions. Here, household resilience is determined by household-level income and food production each month. Surplus post-consumption, computed each simulated month, is a number used as a proxy for resilience in all results. The number must be above a threshold of 0.5 for the household to be classified as resilient. A threshold of 1.5 is used as a determinant of household-level migration decisions (where migration becomes affordable). In this model, migration is seen as “an opportunity to increase household livelihood and food security”; distinct types of migration are defined corresponding to 'opportunistic' and 'needs-based' forms of migration.

Smith (op.cit.) extends the original conceptual model to specify social and farm labour networks in the simulation model - using different information-sharing network size scenarios. Scenarios also explore the impact of changing rainfall patterns on household behaviour and choices, including migration. For each of the scenarios, household resilience classification rates (time series) are compared to a base scenario. The author finds that, because of the interaction of other drivers in the simulation, there is no clear correlation between climate changes and migration. In this study context, low data and epistemic uncertainty is compensated to some extent by checking the model against parameterisations derived from case studies and other literature. He argues that this could limit the extrapolation of findings to other situations.

In this section, and in other comprehensive review studies (Schlüter et al 2012; Miller et al 2010) we have observed that applications of ABM in resilience studies are still relatively few. This is interesting because the approach and its relative merits are by now widely known and have been discussed for a long time, particularly in the area of ecological studies (Bousquet et al 1999; Bousquet and Le Page 2004) and social-ecological systems (Poteete et al 2006; Cumming et al 2010) who suggest that agent-based modelling is a promising way to understand dynamic aspects of ecological systems and networks (cf. Cumming et al 2010). Seemingly, however, there has been no change, or only modest change, in the volume and the focus of simulation studies that address resilience at the individual, social or community levels, in the last 5 years. Accordingly, in the following sections we can give an outlook and make some observations in relation to the current state of the art in simulation modelling.

2.2.1. Outlook

Many researchers – working both in vulnerability and resilience-related disciplines – conceptualise the societies they study in terms of multiple interacting agents and relationships (e.g. Ramos-Martin 2003). Agent-based models therefore may be a natural choice for researchers that would normally adopt an actor-oriented approach in their work. ABMs that aim at historical simulation (e.g. Generative Archaeology models) have been quite successful and well known, (Kohler and Varien 2012, Epstein and 1996) whereas in futures studies they have been applied rather circumspectly. Relatively few articles have been published describing ABMs that consider, for example, climate change adaptation (e.g. Bharwani et al. 2005, Berman et al. 2004).

As a descriptor of an attribute of something (an exposure unit), it can be difficult to formalise vulnerability as a model variable. Consideration must be given to what outcome the entity is vulnerable to, and whether this is presented as a relational variable, or whether the vulnerability is a general concept. The aspects to be included depend on the problem domain. Social vulnerability has many additional complicating features, for example, it is highly dynamic, multi-stressor, operates across scales, and also has significant social stratification. It is difficult to capture this complexity in one single model, to validate the large number of assumptions needed, and to provide summary information presenting the model results.

The outlook, then, is that simulation modelling may deliver a partial picture of resilient communities, systems and individuals, which appears most promising when ABM is included alongside other methods (and other modelling approaches) which are complementary and may facilitate better use of empirical data to inform and constrain the models (Poteete et al 2010: 195) identify four such types of empirical inputs: case-study analysis, laboratory experiments, role-playing games, and observed stylized facts).

Other authors warn us of the difficulties of developing social simulations (Edmonds et al 2013) and the relative lack of use of models (Lucas 2011). In addition to the complication of some of the different concepts in resilience research, discussed above, these observations may throw some light on why there is a relatively low uptake and publication of few new studies. Moreover, some of the barriers are also linked to how ABM is perceived and the critiques it receives (cf. Waldherr and Wijermans 2013). What is apparent is that new methods and tools are needed to address data scarcity and to better recognise the subjectivity within models which will help to counter some of the criticisms.

2.3. Some methodological observations

In this section we consider the use of quantitative indicators in modelling, as well as the prospects for incorporating qualitative field data.

The advantages and disadvantages of quantification approaches to the appraisal of community resilience are discussed in detail in emBRACE Del. 3.5 (Becker et al 2015). The message from this work is that some of emBRACE's "Key Indicators" are directly measurable using a SNM or SNA approach, or other structured subjective methods such as Q-methodology – and changes to these (in terms of an ordinal or nominal scale – that is direction of change) are directly modellable using ABM. This will provide a useful tool for engaging with decision makers, practitioners, and community members.

One of the very active areas in modelling research and related fields is development of methods for incorporating qualitative field data into model specifications in a more rigorous way (cf. JASSS special section, Edmonds 2015). New methods and tools are needed to address data scarcity and to make better use of existing data sets. This is also closely related to the need for better documentation and easier maintenance and re-use of models.

Despite the advances made and the growing appreciation for interdisciplinary, mixed-method approaches, the following remains an open question: What are complementary methods that can be used with ABM to elicit the most suitable data, i.e. in sufficient quantity and quality for design and validation? Further insight into this question is likely to come from approaches that unpack why people behave the way they do, what drives their decisions, their interactions with (social and natural) environments, and of the context that is present in every modelled situation in relation to hazards, risks and disasters.

We return to a further discussion of methods later in this deliverable: the relationship between ABM and other modelling methods and approaches used in the emBRACE project are discussed in more detail in section 4 below.

3. Case studies of ABM

Modelling case studies are different to emBRACE case studies but with an overlap as they focused on smaller (i.e. see Zeitlyn's "partial" – see above) areas or particular aspects of interest to the case studies.

3.1. Disaster preparedness

This modelling case study aims to contribute to a growing literature on preparedness theory, explaining – in a more visual and experimental manner – a part of this theory, specifically Paton's disaster preparedness model (Paton 2003) and community engagement theory of preparedness (Paton 2008), by generating it using an ABM.

The background for increased academic interest in this area is the shift in emergency management from response-based to a risk management focus, in which disaster preparation plays an important role. Within this risk perspective, there has also been a shift towards a focus on development of community capacity to co-exist with acceptable levels of risk and the possibility to grow in face of this risk and benefit from it (Paton 2000).

Empirical research has consistently found that levels of preparedness remain low, even in areas where risk is high, and in spite of provision of information about hazards and how to prepare for them (e.g. Lindell & Perry 1992, Lindell et al 2006 & 2007, Paton and McClure 2013). In other words, knowledge about risks is not translated into preparedness and the adoption of 'desired' adjustment items. Paton's model, like others (e.g. PADM, Lindell and Perry 2011; PrE model, Duval and Mulilis 1999) translates disaster preparedness into a sequence of stages in order to model how people "typically" make decisions about adopting such actions, which resembles the well-known approach more universally formulated as "stage theory".

Becker et al. (2011) state that "An ongoing challenge is to better understand how to motivate people to actually take action and get prepared". To meet this need, both qualitative and quantitative approaches have been used to identify important aspects. Although there always turns out to be numerous factors, more than any single model or explanation can fully incorporate, relationships between some stages of preparedness are understood quite well. In the case of Paton's model, similar patterns have now been identified across different studies – largely by Douglas Paton himself – and his model, and its applications, will be discussed below.

3.1.1 Data and case study

Data collected in the emBRACE Turkish scase study and discussed in METU's case study deliverable (Karanci et al 2014) is extensive on individual psychological resilience, and on response, recovery and reconstruction processes as perceived by different stakeholders. Researchers used a mix of qualitative and quantitative methods. A set of focus groups were carried out with actors from various organizations/ institutions. Data also include semi-structured interviews plus in-depth interviews with 20 actors (disaster survivors) in Van, as well as quantitative survey data, which were used in statistical analysis.

Models used were the Multivariate Risk Factor (MRF) model of Freedy, Resnick and Kilpatrick (1993), which includes many pre-disaster factors. A second model (not used in the Turkish empirical study) is the disaster preparedness (DP) model of Paton and colleagues, which is discussed at length in emBRACE Del.4.1, focusing on individual and household-level resilience (Karanci, Ikizer and Doğulu 2015). Also, in Van although the main focus was on the individual, the research also connected with community factors and analysed the perception of community resilience. Main findings were the identification of key predictors of individual psychological resilience, as well as the qualitative findings, e.g. how the Marmara earthquake may have influenced how the response and recovery operations were managed. The qualitative study concluded, based on the focus group qualitative content analysis, that discussion evolved around "...common topics, namely, increased awareness on earthquake safety of buildings, increased interest in mandatory earthquake insurance for buildings, economic recession in the post-quake period, and change in values and attitudes of the community members".

3.1.2. Methodology and rationale

An ABM was developed based on a series of papers published by Douglas Paton and colleagues (Paton 2003; Paton, Smith and Johnston 2005, Paton 2008; Paton and Johnston 2008) which explain the preparedness model and different variations of it. It was then critiqued in relation to emBRACE case study work in Turkey, as Paton's model was important for METU's work on individuals' perceptions of resilience relating to preparedness. As discussed above, some data were also available from project studies in Van and Adapazari/Sakarya (and also referred back to other events e.g. Marmara). However, as discussed below the ABM is only loosely connected with this empirical work. The ABM was developed in several stages. It was developed by SEI and discussed with colleagues at METU. The team at METU was not experienced with ABM but became more interested as the work progressed. Some ideas for 'scenarios' to explore with the ABM are based on the case study work in Turkey and are discussed in a later section.

We used NetLogo (Wilensky 1999) modelling software to implement the model. NetLogo is a high-level, open source, cross-platform programming language which developed from an educational domain and is now one of the most widely used platforms for ABM research. R statistical programming (R Core Team 2015) was used for the analysis. R is one of the most widely used tools for computational statistics, visualization and data science. There is also the package 'Rnetlogo' available for R which makes it possible to use the two applications jointly by exchanging commands and data. The simulations were run from Rnetlogo.

In the next section a single example simulation is presented first. Then, a set of sensitivity analysis tests are carried out across different parameter settings with replicate simulations. For each experiment, 51 runs were made with different random seeds and then averages of the outputs were calculated. This number, 51, was chosen because each experiment could be completed in around 1 hour of PC time and because the median values (calculated for the counts of the number of agents) would be integer valued.

The main outcome of interest for testing the model is the individual actors' intention to prepare. From a socio-cognitive perspective, intention to prepare is thought to be a key predictor of actual preparation, where actual preparation is often the desired adaptive responses from point of view of risk reduction. Paton et al (2005) note: “That intention played a prominent mediating role in the model proved to be a highly significant element of the model.” In the same paper the author defines a key element of adaptive response to adversity as “the ability of communities to draw on internal personal and social resources”. They continues: “This makes preparation, the process by which resource availability is encouraged, and important component of resilience.”

In the Turkish case study of emBRACE, the partners investigated resilience in the context of earthquake events, particularly using a psychological lens and mixed methods approach. For example in Van, beliefs were identified and quantified across the respondent group, allowing categorisation of the typical, variant and rare responses. In this study, socio-cognitive factors came out strongly as important aspects of resilience, both qualitatively and quantitatively. These factors were not captured as individual-level variables which could also have been useful for modelling. We could not obtain quantitative values from interview respondents; we do, however, have some qualitative/categorical data to compare with the distributions for model variables, such as risk perceptions. This is sufficient to explore whether the simulation model produces outputs that reflect what has been observed in Van.

Another variable used in the quantitative study in Van as an outcome (dependent) variable was stress-coping ability. In relation to the DP model, stress-coping ability seems to be closely related to the individual’s ability to manage hazard anxiety at high levels (avoiding denial and) and indicating healthy psychological functioning.

An initial assumption for this model is that communication is in accordance with the deficit model of hazard information (see section 3.1.6) which has the usual components, i.e. source, message, target. However, we also look at some critiques of this model with the aim of improving how communication is considered and how it is modelled. Other findings can be drawn from literature. For example, Becker et al. (2011) focuses on people’s use of information. According to Becker et al. (2011), among passive forms, information in brochures may be more difficult to recall than TV visual images.

Intention to prepare has been identified as an important variable, and appears to be a good candidate for understanding personal disaster resilience, albeit it is only part of the story. In this modelling work we decided to investigate this partial picture of resilience, selecting only one 'output' variable, using the DP framework to consider it detail, and from a dynamic perspective with ABM.

Paton's model argues that preparedness represents the outcome of a three stage reasoning process: motivation to prepare; forming intentions to prepare, and their conversion into actual preparation (Paton 2003). The ABM was developed to show the interaction of several of the variables in the precursor stage that are thought to affect intentions. In particular we wanted to extend the static picture of preparedness to include a more time-dependent analysis. This may be useful in thinking about what type of disaster preparedness measures are attainable over different time periods, and also how this might scale across a heterogeneous population.

The time analysis of intention to prepare shows which actors are ready to accept which kind of preparedness measures, and therefore its signature – the output of the simulation – could indicate resilience or lack of resilience. The importance of time, as a moderating factor, was demonstrated by Paton et al. (2005) using regression analysis within structural equation modelling. In the study the variable included was the time frame within which people estimate or assume that the next hazard event will occur. Including time within a simulation of a preparation process, where the actual mechanism is considered, has not so far been considered. The next section describes the agent-based model and the simulation experiments carried out with the model.

3.1.4. Model description and simulation experiments

An ABM, based on the Paton 2003 conceptual model of disaster preparedness, was developed and explored through simulation experiments. The ABM was developed to show the interaction of several of the variables in the precursor stage that are thought to affect intentions. The scope of this model is limited: the outcome of interest is only the intention to prepare (i.e. the first two stages of the conceptual model of Paton). Variables linking intentions to other factors that are thought to moderate how intentions lead to preparedness are not included (although they could be included in a future version).

The simulation model also includes a simple social network in which messages related to intentions are transmitted. The time step for the model is the week – an approximate correspondence with a real time frame. Each week time step in the model is broken down into 4 sub-steps in which agents:

- update network connections
- send, receive and process messages
- calculate risk, and expectations (beliefs)
- formulate intentions

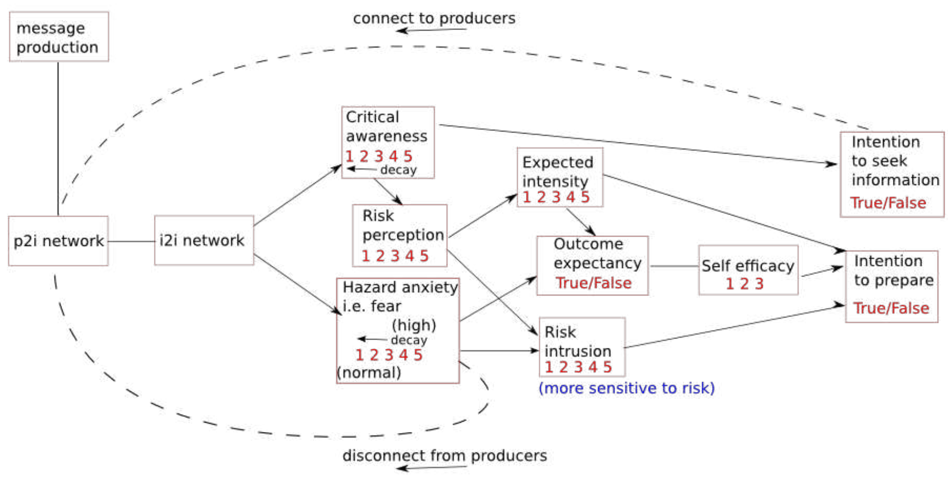

Figure 3.1.1: Overview model conceptual diagram, showing key model variables and relationships. Values of model variables, assuming integer scales, are shown in red.

This section, model description, provides details on all of the variables at precursor, mediator, and intention formation stages as well as the network aspects depicted in Fig 3.1.1.

Precursor variables; Critical awareness, Risk perception and Hazard anxiety.

Critical awareness is 'the extent to which people think and talk about the hazard' similar to 'hazard intrusion' which depends on a person's knowledge/experience gained through previous exposure to the hazard and hazard information (especially through interactive activities). In the model, awareness (an integer between 1 and 5) can be increased when suitable messages are received from the producer/individual networks. Awareness decays after a number of time-steps (decay-rate) if no further messages have been received (saliency is zero).

Risk perception is an overall estimate across low frequency/large events and high frequency/small events of damages. We assume that risk is underestimated by individuals, but we assume that the reliability of the estimate improves with critical awareness (therefore risk perception increases towards the 'real' value – we also assume here there is an 'objective' risk, which could be assumed to be fixed number in the simplest case – but that perceived risk does not exceed real risk[2]). Therefore, in the model, perceived risk changes with critical awareness.

Hazard anxiety, is a measure of fear which combines concern for magnitude of the hazard and its consequences and for impending occurrence. Anxiety precursor has two different effects because at moderate levels it can motivate to prepare and at high levels it can impede the intention formation, and both are captured in the model. Low and moderate levels influence via a variable called risk intrusion, whereas at high levels of fear the ability to function normally can be compromised via a link to outcome expectancy (if hazard anxiety exceeds a tolerance level the expectancy that the event can be mitigated is false). This precursor at high levels also causes the individual to disconnect from producers. Similarly to Critical Awareness, the level of anxiety decays after a number of time-steps (decay-rate) if no further messages have been received (saliency is zero).

Mediator variables: beliefs which mediate between precursors and intentions:

Expected Intensity is a measure of the severity of the anticipated hazard. It is closely related to perceived risk by further specifying the magnitude of the event (i.e. large or small) that the individual is anticipating, and potentially, preparing for. Expected Intensity is initialised as an integer value drawn from a random uniform distribution with minimum 1 and maximum equal to the risk perception. When an individual's risk perception changes, Expected Intensity is updated.

Outcome Expectancy is a belief about whether a community will be able to respond effectively to a hazard and reduce risk. It depends on two input variables and two corresponding thresholds. Firstly, if anxiety is above the anxiety threshold, then it is assumed that the hazard will exceed response capacity and therefore nothing can be done (the problem is irreducible) and this variable is set False (preparation is subsequently not worth being pursued). Otherwise, Outcome Expectancy depends on comparing the Expected Intensity with the idealised community response efficacy (a fixed integer) and if the Expected Intensity is less or equal to the available response then the Expectancy is set as True.

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2 This state of affairs does not necessarily reflect 'reality' but is a device necessary for the modelling process. Further, though, the fact that the model has this characteristic is useful in discussion to what extent this – and other characteristics within the model – is (or is not) reflective of real life situations.

Risk Intrusion is a variable proposed that captures the extent to which an individual factors risk into their intentions to prepare. It is based on the idea that some level of anxiety is necessary; the higher the anxiety the more likely one is to be motivated prepare. Paton states that anxiety makes people more sensitive to risk, and this is captured as 'intrusion of risk into planning'. Risk Intrusion is a function of Risk Perception and Hazard Anxiety. It is compared with a risk tolerance threshold to establish whether current risks might lead to intentions to prepare.

Self-efficacy is, similarly to the (idealised) community response efficacy, a belief about the possession of sufficient capacity to respond, and it operates at the personal level of individuals. It is a key variable in Paton's and other models. In the ABM, individuals each have a fixed value of this variable, and it is compared with the Expected Intensity to inform the intention. If Self-efficacy is lower (i.e., is not adequate for meeting the intensity) then the individual does not feel capable of response, and therefore will not form intention to prepare.

Intention formation variables: model outcomes taking values True or False:

Intention to prepare is one of the main outcomes of interest in the Paton model, and there are several mediating variables that can influence the formation of such intentions: here, direct influence comes from expected intensity and self-efficacy (which are compared, as explained above) and from Risk Intrusion (which is compared with risk-tolerance). If Self-efficacy and Risk Intrusion are both sufficiently above corresponding thresholds, then the individual will form the intention to prepare. Conversely, if either of these preconditions does not hold then the individual will not form the intention to prepare.

Intention to seek information is influenced directly only by the Critical Awareness. It is positively influenced, i.e. if Critical Awareness is above the awareness threshold, then the individual will form the intention to seek information. As we will see, this involves connecting to further producers and becoming exposed to potential additional messages, which is somewhat circular (messages can raise awareness). Also, however, if the individual is in the state of disconnecting (has high anxiety above the threshold) the individual will not add any links [Not shown on the diagram].

Network variables: generation of social networks and their function:

Message Production: Messages are part of the environment in which individuals operate and to which they respond. They are key to the social interactions in our model, and they allow us to investigate the emergence of outcomes within a social system and including dynamics of the disaster preparedness model. When the simulation is initialised, a set of messages is created. Then, in each time-step, message production occurs: each producer agent selects a different message and broadcasts it via all of its connections to individuals (p2i network). Messages can cause changes in values of certain individual's variables (Critical Awareness, Hazard Anxiety) when they are processed.

The p2i network is set up initially with few connections between producers and individuals. The set of links of the network then evolves – the network structure is changed by connecting and disconnecting. Message production influences the network content and therefore the interactions. The p2i network also influences the network of connections among individuals (i2i network) because it influences the content. Some messages produced in the p2i are then sent from individual to individual through these connections (there are a number of 'rounds' of i2i communication but the messages do not persist in the network from one time-step to another). The i2i network also influences the precursor variables Critical Awareness and Hazard Anxiety.

Recording model output variables

Intention to prepare over time is the main output variable of interest in the model. In its raw form this is a binary value, True or False, measured at every tick. However, rather than report the time series evolution of this model variable, or simply report a total number of weeks ,we defined 4 categories which typify different kinds of response:

(i.e., 0 = L0; 1<=L1<=6 ; 7<=L2<=33 ; 34<=L3<<=52)

In other words L0 contains the set of individuals who formed no intentions to prepare, L1 those who intended to prepare between 1 and 6 weeks during the year, etc. This categorization makes it easier to understand preparedness over a population across a longer period of time, which would be more relevant for some sorts of interventions. To give examples to make this point more concrete, individuals categorised in L1 might be able to benefit undertaking very infrequent or occasional preparedness activities, such as securing heavy items of furniture or inspecting building structures. Individuals in L3 and L4 might be candidates for targeting some types of preparedness measures requiring high vigilance, such as testing safety equipment and stocking emergency supplies of food. This could be a useful distinction because information about how many individuals there are in each category may help a planner anticipate what sort of strategy (for enhancing preparedness) may be effective. For example providing high-maintenance safety equipment may not be the best strategy if most of the population is in L0 and L1. Thus it could help understand who would benefit from different interventions and possibly help to prioritise those.

Simulation experiments

An initial experiment was done with base parameters. Then, a set of 5 simulation experiments were carried out to better understand the effect of different model parameters on results. We investigated four parameters in the category of motivating factors – critical awareness, hazard anxiety, risk perception, underlying risk – and one parameter in the category of moderator variables – self-efficacy – which affect indirectly intentions to prepare. For most of these variables we focused on examining the thresholds for behavioural change.

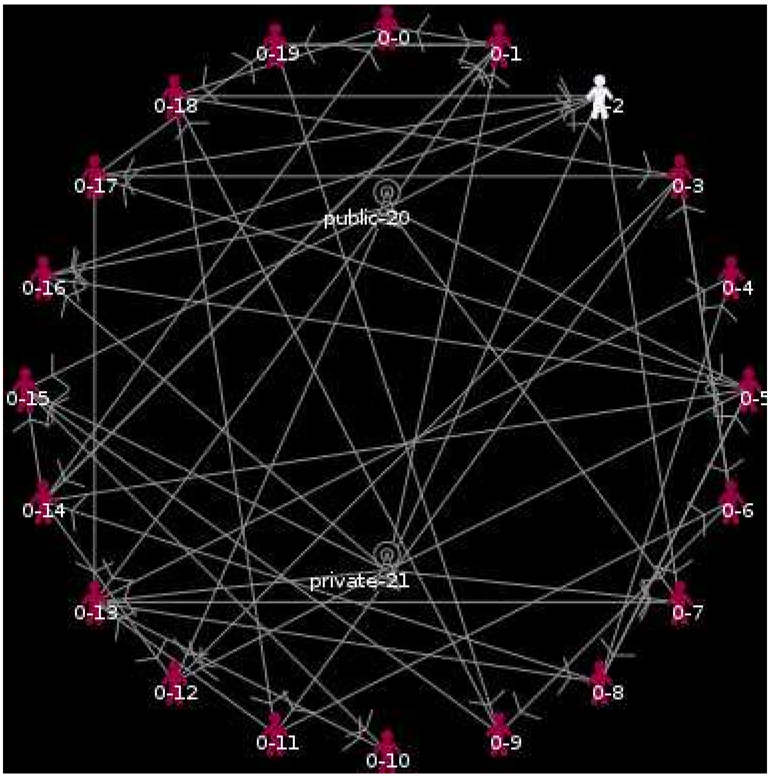

Figure 3.1.2: screen shot of the simulation

In each experiment the model is set up with 20 individuals and 2 producers that also comprise a communication network (see Figure 3.1.2 above). The outcome of interest for the experiment is the indication of how many individuals form intentions to prepare and for how long they remain in this state over a specific period, i.e. one model year. We recorded the result by running the model for an initial spin-up time of 2 x 52 weeks (i.e. two warm-up years), and then for a further 52 weeks after which a set of measurement values was returned. We monitored the state of each agent during the final period of 52 weeks and used the result to calculate incidence of adopting preparation intentions.

3.1.5. Results

An initial experiment serves to illustrate the model parameter set up and the analysis of outputs. In this experiment the parameter set is shown on the left and the result is shown on the right hand panel. This was produced with one single simulation run.

Base parameters:
set fear-t-levels [3 4 5]
set aware-t-levels [2 3 4]
set risk-t-levels [3 4]
set underlyingrisk 4
set selfefflevels [1 2 3]
set decay-rate 5
set i2i-rounds 1

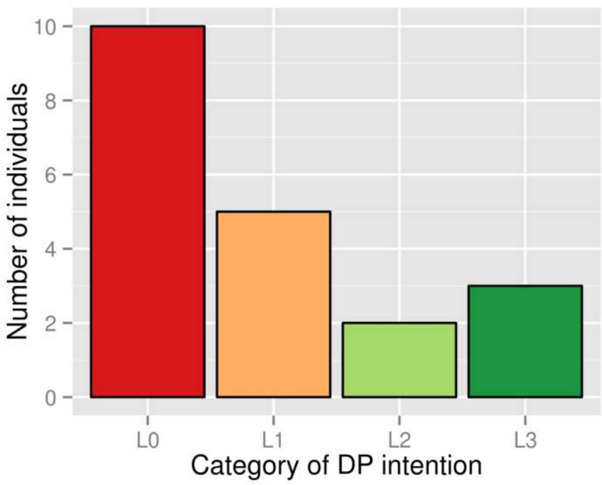

Figure 3.1.3: initial experiment

As described above, we assigned individuals to categories based on their preparation intentions among the four categories L0, L1, L2 and L3, (L0 being highest and L4 being highest). To recap: individuals assigned to category L0 never formed any intention to prepare; individuals assigned to L1 had the intention to prepare for between 1 and 6 weeks; in L2 for between 7 and 33; in L3 for between 34 and 52 weeks. Plotting the frequency distribution across these categories provides a resulting signature of the simulation (Fig 3.1.3). In this particular experimental run, half - 10 individuals - never formed any intentions to prepare (L0), whereas five individuals occasionally had the intention (L1) and two individuals moderately frequently (L2). Only three consistently had intentions to prepare, for most of the time throughout the year (L3). Plotting this signature produces a parabolic curve with relatively more individuals in L0 followed by L3.

The simulation experiments involve doing many replications with different values for the initialisation of the selected parameters. In the first experiment, labelled S1, we vary the hazard anxiety threshold (fear threshold). This is initialised by drawing values from a uniform (integer) distribution for each agent in the simulation. We vary the way the uniform distribution is constructed, firstly constructing it from the interval (4,5) and then subsequently including lower values in the interval (3,4,5), (2,3,4,5) and (1,2,3,4,5), meaning that in the later sets of replications, the agents will be likely to have lower hazard anxiety thresholds and there will be a wider range of values. All other parameter settings are identical, so in Fig 3.1.4 we can compare the effect of the changes in the hazard anxiety threshold.

The results are shown differently to the frequency histogram in Fig 3.1.3. Rather than a histogram, boxplots are used to illustrate the results distribution and median values over 51 simulations. The central bar shows the median (also reported in the table 3.1), top and bottom of the bar show the Q1 and Q3 statistics, and whiskers on the bar show the min. and max. range. Looking at the median values, one can see the relatively higher frequency in L0 and L3. Multiple panels are used to show differences in outputs with different parameter values labelled at the tops of each panel.

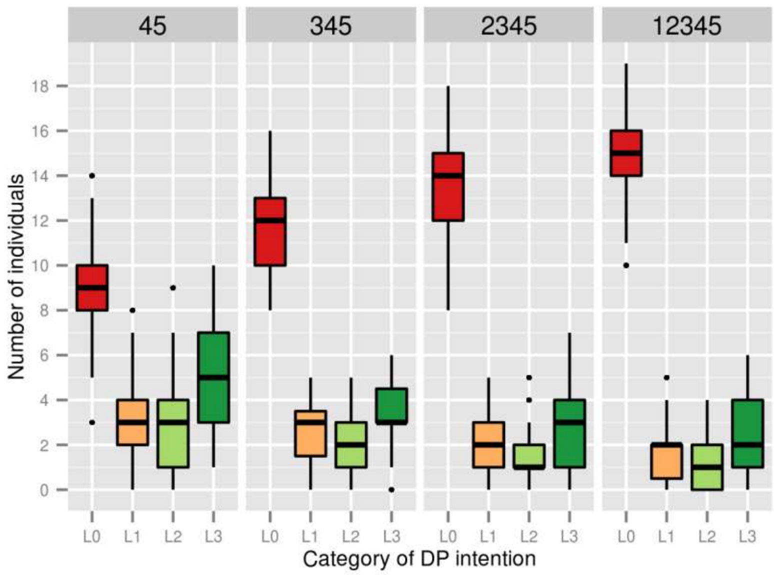

Figure 3.1.4: hazard anxiety

In the S1 experiment, first panel shows the hazard anxiety threshold is drawn from the interval (4,5). The result is that around half of the agents (median = 9) never develop the intention to prepare, L0. Around 3 of the agents fall into each of the L1 and L2 response categories, and around 5 agents in L3, although there is quite a lot of variation across replications. In contrast, in the case where the interval (3,4,5) is used (second panel from the left), more than half, around 12, agents are in L0 and their occurrences in L1, L2 and L3 are lower. In the third panel and fourth panel this difference between heights of the bars increases – very few agents (around 5 or 6) form any intention to prepare over the entire time period. To sum up, higher anxiety threshold levels (interval (4,5)) encourage greater incidence of disaster preparedness intention than low anxiety thresholds (the interval (1,2,3,4,5)).

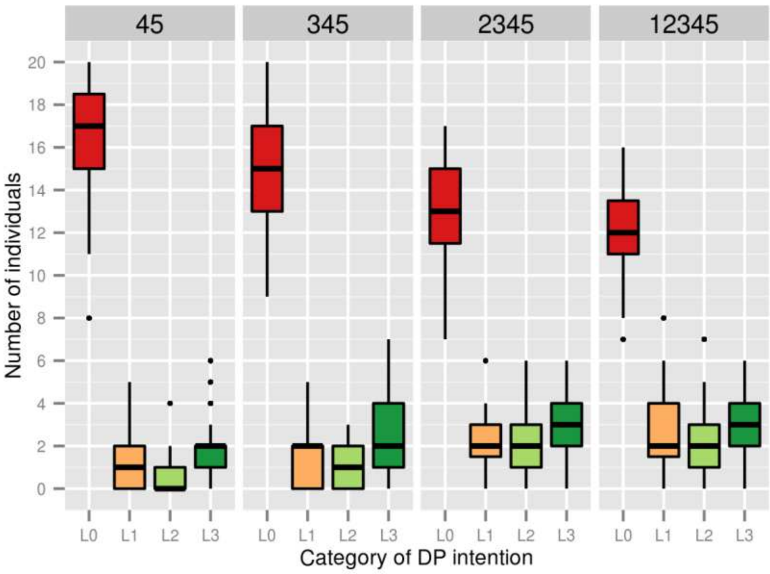

Figure 3.1.5: critical awareness

In experiment S2, we varied the critical awareness threshold in a similar way to the anxiety threshold described earlier. The intervals were again varied from (4,5) to (1,2,3,4,5). The results can be seen in Fig 3.1.5 above, and the intervals used can be seen in the panel labels. In the case (4,5), a median of 17 agents (85% of population) never formed the intention to prepare (L0) whilst very few were classified into L1, L2 or L3 (medians of 1, 0 and 2 respectively). In the second and third panel the picture looks a little better, as more agents are joining L1, L2 or L3 (medians of 2, 1 and 2) meaning more agents are forming intentions over some part of the time period.

However more than half (median 12 in the fourth panel) are still never forming such intentions. To sum up, lower critical awareness threshold levels (using the interval (1,2,3,4,5)) encourage greater incidence of disaster preparedness intention than high awareness thresholds (from the interval (4,5)).

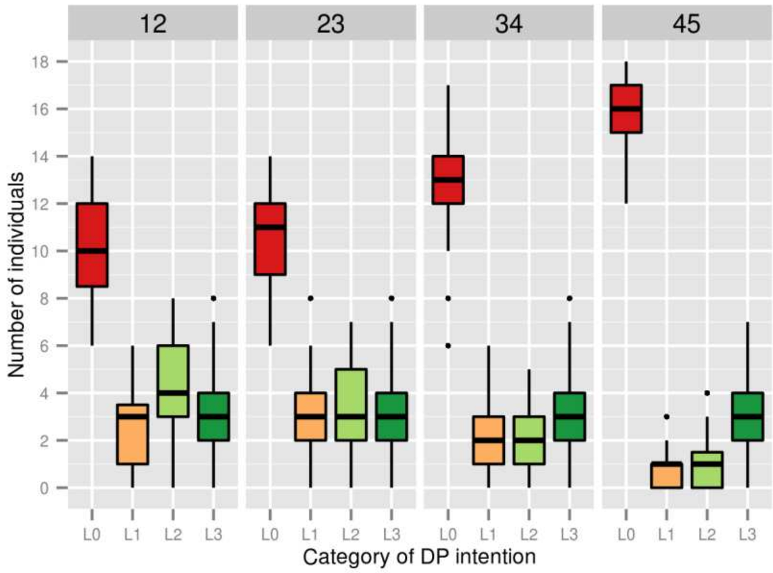

Figure 3.1.6: risk tolerance

Experiment S3 investigated the risk tolerance threshold. In a similar way to the above, the parameter distribution was varied using the intervals (1,2), (2,3), (3,4) and (4,5). Thus the risk tolerance threshold increases looking at the panels from left to right in Fig 3.1.6. Higher risk tolerance threshold means that risk perception (moderated by hazard anxiety) of agents needs to reach a high level before it may lead to intentions to prepare (see model overview). In the figure on the left panel, where the threshold is lower, around half of the agents never form intentions to prepare, whereas a small number form intentions over few weeks (L1), more agents over a moderate time frame (L2), and few again over 34-52 weeks (L3). As we increase the risk tolerance, intentions to prepare become more scarce, as could be expected. In the right-hand panel, few actors are classified in L1 and L2 whereas the median in L0 increases to 16 actors. This simulation has confirmed that risk tolerance it is an important factor over the intervals tested.

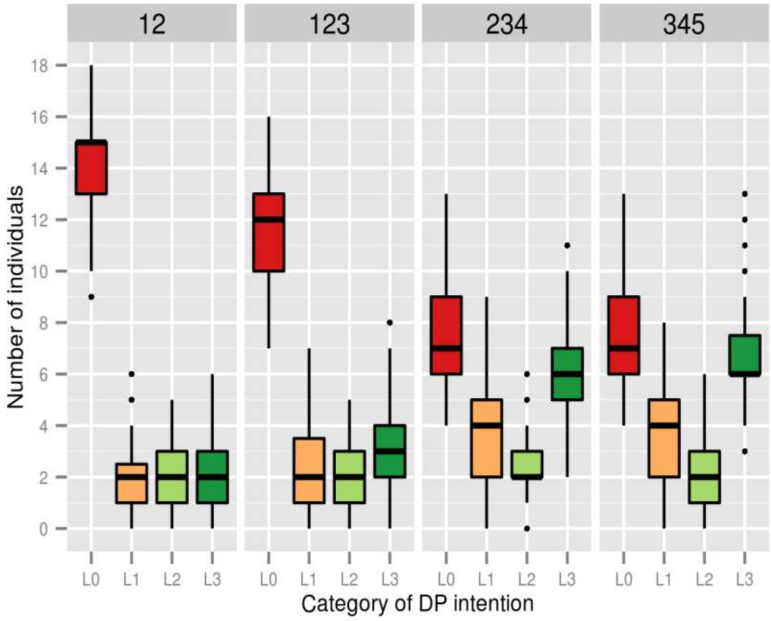

Figure 3.1.7: self-efficacy

In simulation experiment S4, self-efficacy was investigated. Self-efficacy was modelled as a fixed attribute which is important for moderating expectancy; the higher the self-efficacy, the more a person believes he/she personally could affect adequate preparation. In the model it is compared with expected intensity. It is not surprising that results show that lower expected intensity predicts lower preparation quite well. In Fig 3.1.7 above there is a strong contrast between the second and third panels, with respective intervals (1,2,3) and (2,3,4). The median result shifts from 12 in L0 (second panel) to 7 in L0 (third panel) and from 3 in L3 (second panel) to 6 in L3 (third panel). This shows that the results are very sensitive to changing this parameter around certain values. The final panel shows that outcomes are not sensitive at the higher range of values (3,4,5).

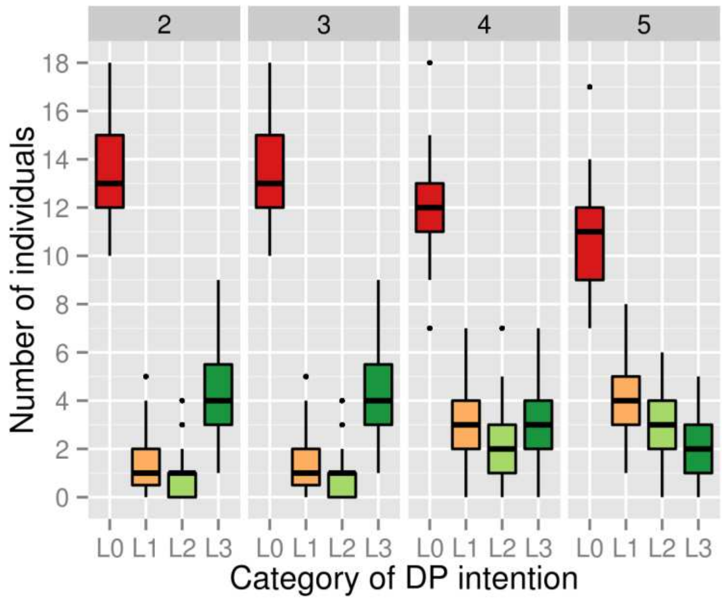

Figure 3.1.8: underlying risk

Experiment S5 shows the changes to simulation outcomes varying the underlying risk parameter, where underlying risk is assumed to be uniform for the whole population. Fig 3.1.8 shows that the model is not as sensitive to this parameter as some of the other parameters tested. What is noticeable is that the shape of the profile changes from a parabola shape at low values of u-risk to a monotonic curve at high values – with fewer agents in L3 and more agents in L2, L1 and L0. However the median number of agents in L0 does not change very much.

The five experimental outputs can be summarised in the following table, which reports the mean values of each experiment, in Table 3.1.2.

	Panel 1				Panel 2				Panel 3				Panel 4			
Cat.	L0	L1	L2	L3	L0	L1	L2	L3	L0	L1	L2	L3	L0	L1	L2	L3
S1.fear-t	9	3	3	5	12	3	2	3	14	2	1	3	15	2	1	2
S2.aware-t	17	1	0	2	15	2	1	2	13	2	2	3	12	2	2	3
S3.risk-t	10	3	4	3	11	3	3	3	13	2	2	3	16	1	1	3
S4.selfeff	15	2	2	2	12	2	2	3	7	4	2	6	7	4	2	6
S5.u-risk	13	1	1	4	13	1	1	4	12	3	2	3	11	4	3	2

Table 3.1.2: means of simulation experiments

3.1.5. Discussion & lessons learned

Considering that, in general, improved preparedness should correspond to a pattern with more L3, L2 and L1 outcomes, and this is linked to strengthened resilience, we can now identify which parameter range supports this 'best' outcome in terms of intentions to prepare. An initial look at five model parameters showed that:

1. lower critical awareness threshold levels (the interval (1,2,3,4,5)) encourages greater incidence of disaster preparedness intention than high awareness thresholds (from the interval (4,5))
2. higher anxiety threshold levels (interval (4,5)) encourages greater incidence of disaster preparedness intention than low anxiety thresholds (the interval (1,2,3,4,5))
3. lower risk tolerance thresholds (interval (1,2)) encourages greater incidence of disaster preparedness intention than high risk tolerance thresholds (interval (4,5))
4. lower self-efficacy levels (the interval (1,2)) results in lower disaster preparedness intention than higher self-efficacy levels (the interval (1,2,3))
5. higher underlying risk (5) produces disaster preparedness intention levels falling more in the L1 L2 and L3 and less in L0 and L4 than low u-risk (1)

The patterns were all quite strong and significant, and they are for the most part easily explainable and expected results. There was some variation between the replications of each experiment, which is usual. It also revealed that changing these parameters slightly can often make a large difference to the results. The experiments above have systematically explored the model to identify some of these sensitivities.

We should point out that some of these variables, such as intentions, may be difficult to measure. Measurements used by Paton included items that assessed peoples' intention to increase actual preparedness (Paton et al 2005) however the measuring system and questions asked are not reported in these publications. Paton and Johnson (2008) discuss the inclusion of intention variables and the advantage of taking measurements of this in order to help understand preparedness: "the assessment of intentions can thus provide an indication of people's potential to act. It also represents a more stable indicator since it is less susceptible to bias or moderation by factors such as beliefs regarding the timing of the next hazard event or resource availability" (op.cit.).

Further research could investigate refinement and potential application of this model. If the model seems to be behaving as expected, at least in terms of the direction of the changes, it can potentially be more useful to increase the complexity and study further some of the important questions identified earlier.

A limitation of the model is in terms of the determination of appropriate inputs to the model. Parameter values should be chosen to more closely match data from case studies or other evidence, such as stylized facts. Further experiments could also be carried out based on stakeholder priorities, for example scenarios they are interested in. Other limitations are in terms of the relative simplicity of the message model, the relatively static social network used, and relatively small scale of the simulation. Some of these issues will be explored further below.

3.1.6. Comparison with analysis in Van

One striking feature of the Van data (obtained from interviews with disaster survivors) is that whilst some respondents reported awareness of the hazard risk (n=7), many more did not (n=12) (seismic risk; Karanci et al 2014: 84). The variation in responses is somewhat surprising considering shared backgrounds of the interviewees. The excerpts further show that a range of factors that could affect the decision-making process, including precursive or motivating ones. The primary analysis in the case study thus provides information about respondents' assessment of personal risk, and this relates to the 'risk perception' variable in the DP model (it is less about critical awareness – how people think and talk about hazards and their knowledge of / capability to carry out effective preparation actions).

Possible reasons for the lack of quake awareness (seismic risk), include the well-established idea that a person's risk perception is often influenced by that individual's own attitudes more than by the recognition of relevant hazard information (Sjöberg 2000). On the other hand, lack of risk assessment information and the ability to provide it to residents could also explain low risk perception, as could a lack of trust in the information or in the sources of that information. Finally, we can consider that the hazard/risk info simply does not register because it is difficult to achieve saliency and communications are often inadequate to do so, for example Becker et al. (2011) finds that passive information is often not very effective.

Nevertheless, the reality of risk perception, which is obviously complex, contrasts strikingly with the simulation in which the risk perception variable tends to follow a high/low fluctuating pattern. Fig 3.1.9 And Fig 3.1.10 show time series of the risk perception and awareness respectively for every agent over a period of 20 ticks following simulation spin-up. This was produced with parameter set : fear-t-levels (3,4), aware-t-levels (2,3), risk-t-levels (3,4), underlyingrisk = 4 , selfefflevels (1,2,3), decay-rate 5.

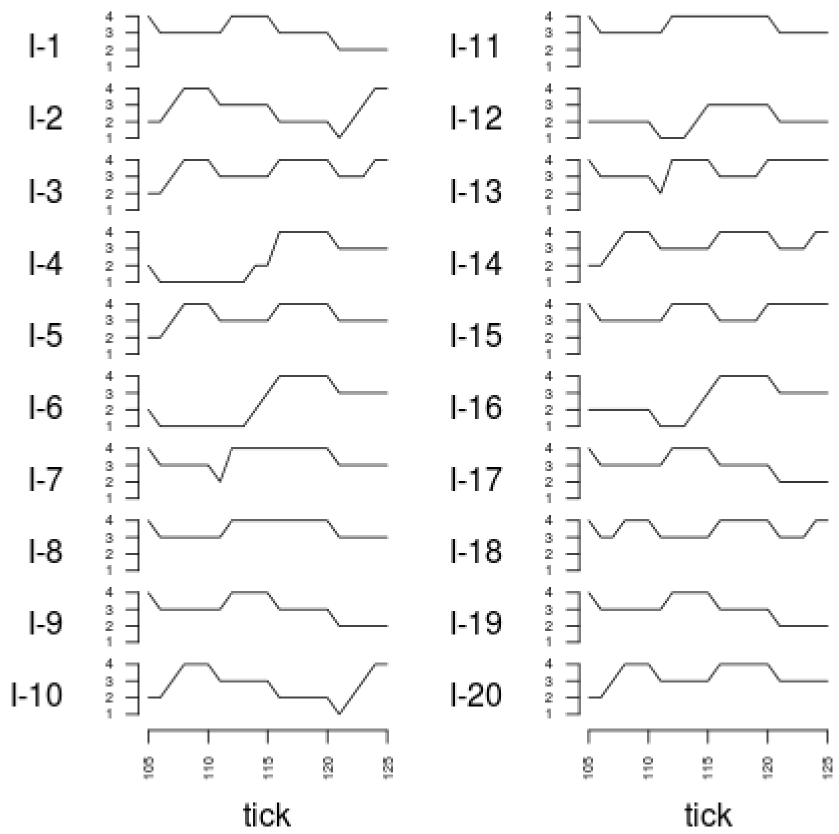

Figure 3.1.9: evolution of the risk-p variable across the population

Over this period, 20 ticks, or weeks, one sees fluctuation between different integer-valued levels of risk. For example agent I-18 fluctuates between medium (3) to high levels (4) whereas agent I-6 moves rapidly from low (1) to high (4). The mean level of risk ranges from 2.4 (in tick 106) to 3.55 (in tick 120).

This finding that risk-p variable in the model fluctuates around a relatively high mean value should, however, be considered against the case-study finding that actual risk perception is reportedly low in Van (n=12), which suggests some changes to the model may be needed. We could consider using an alternative message model which includes a more realistic consideration of risk communication mechanisms.

This may be better suited for exploring the case of low risk perception, this important precursor variable in the model.

Another apparent limitation, evident in time-series simulation results, is that risk-perception in the model agents arguably changes too quickly and may be unrealistic. In general, we do not know how quickly changes in perceptions occur (the only information relevant to this point originating from emBRACE case studies in Van (Turkey) and in Badia (Italy), suggests that people certainly get better informed about risks ***after*** hazard events occur).

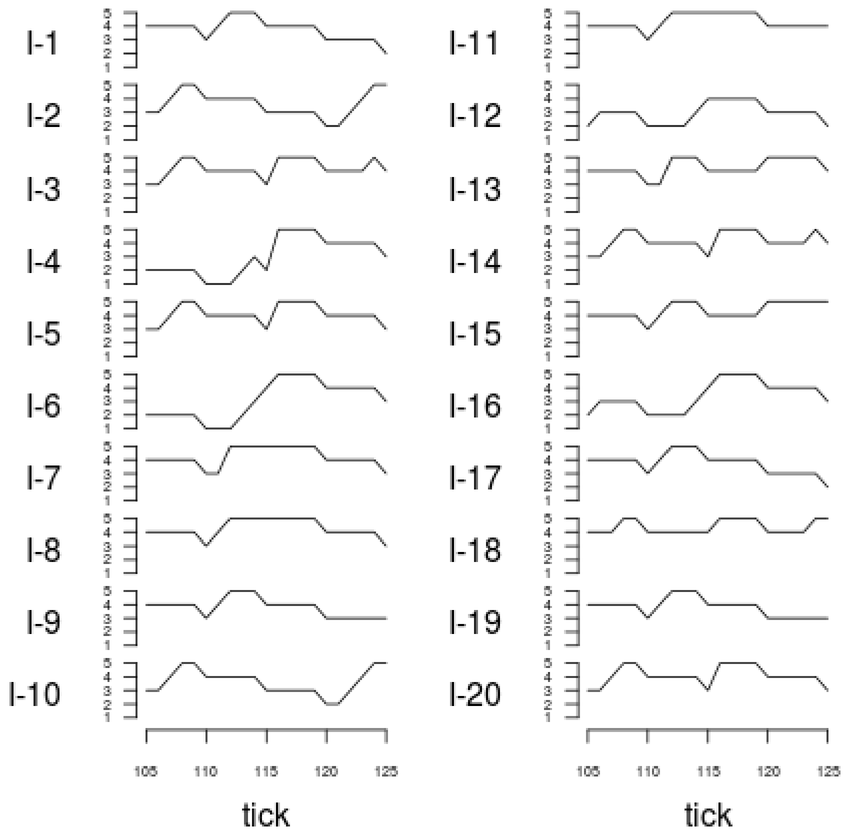

Figure 3.1.10: evolution of the awareness variable across the population

Awareness values also vary over time and across the population. In many cases, the pattern looks similar to the earlier figure, and this would not be surprising because higher critical awareness can lead to improved risk perception. Awareness varies between a low value of 1 and highest value of 5 with a low mean of 3.05 in tick 110 and a high mean of 4.45 in ticks 116-119. As with risk perception it would be interesting to obtain some data with which to study awareness further.

In Van, among the factors that survivors themselves used to characterise disaster resilient communities, were quake awareness and disaster preparedness, although the most important characteristic was social solidarity and cooperation (Karanci et al 2014: 103). However another relevant passage is “Having high risk perception, disaster awareness, knowing and being sensitive to risks [...] were seen as important boosters of resilience.” (ibid: 26).

Evidence from the Turkish case study shows that experience of a previous disaster is important for improving response capacity (response forces are strengthened and can be assigned to the emergency operation, as they were in Marmara). Experiential information is critical for establishing trust in information and information sources. Although it is mainly linked with disaster response, previous experience can also be important for disaster preparation. Analysis of the case study work in Badia in South Tyrol shows that respondents who were personally affected or had direct contact through their involvement in the clean-up operation were more likely to perceive higher risks of landslides and had higher levels of disaster awareness (Pedoth et al 2015: 37-40).

In general, however, the potential influence of previous experience (i.e. Marmara, or the previous large earthquake in Van in 1976) on critical awareness in Van seemed to be reduced by the temporal and spatial remoteness of earlier events, and may only have played a minor role. However, the assumption is backed up by empirical studies, for example by Paton et al. (2000) who found in individuals “that experienced consequences directly that positive shifts in threat knowledge and risk perception were evident” and in terms of the significance of this variable when applying the DP model (Becker et al 2011: 4-5).

Discussing the impact of the event in Van itself, the report (Karanci 2014) mentions attitudinal changes to risk and risk avoidance; there are respondents’ reports of “an increase in awareness in the community about disaster risk and responsiveness”. Preparedness strategies such as stocking necessary supplies are mentioned. The inclusion of experienced agents – those that have different perceptions of and attitudes towards hazards – into this model would be an area for further exploration. Alternatively there is the possibility to study the emergence of hazard experience through the inclusion of shocks (see Filatova and Polhill 2012).

Reflecting on the Van case, and other discussion about communication of hazard information which is part of the emBRACE work on social learning (reported in

Pelling et al 2015), the message model should ideally also be updated to emphasise a wider range of factors impacting personal perception of risk.

In emBRACE Deliverable 4.3 (Pelling et al 2015), (and also in Deliverable 5.5 (Grimmond et al 2014) two different mechanisms for communication/diffusion are contrasted. First, the direct dissemination of information which includes methods such as mass media campaigns. This involves expert knowledge and is communicated in terms of advice about how to respond to risks. It is sometimes referred to as the 'risk-communication deficit model' because it is based on the assumption that expert knowledge is the more valid for transmitting risk messages without bias or distortion. In this model learning is based on closing a knowledge deficit gap, to improve understandings of non-experts.

This should be contrasted with what is thought to take place in communities, especially those that are disaster resilient. This second type is characterised as a 'learning model' of risk communication which incorporates the idea that non-experts are involved in adapting and sharing knowledge as well as generating additional knowledge. It is suggested this involves the "opinion leaders or mavens disseminating information and demonstrating the desired change..." (Pelling et al 2014: 16)

This links to the idea of information retention in risk communication. Gladwell (2000) popularised the idea of stickiness of a message as well as the role of opinion leaders or mavens. In his view often both components need to be present in order for an idea or instruction to be transmitted successfully. In this model, social learning is based on an individual's curiosity, drive to learn, reflect and adapt. The message is personalised and made relevant, and importantly, can be inspiring to a recipient, inviting the sharing of collective knowledge. Retention is enhanced by many of the same factors.

3.1.7. Analysis of Interventions in Van

One of the most interesting areas of study for emBRACE work on earthquake hazards in Turkey is researching the changes observed in disaster risk management between the 1999 Marmara event and the 2011 Van event. Considering state interventions, emBRACE Del. 5.3 (Karanci 2014) concluded that participants perceived improvements in disaster response capacity (search and rescue, mobile health services and psychological support) but also interventions in risk minimisation (improved construction and land use regulation). The report also mentions several times the Turkish Catastrophe Insurance Plan (TCIP), which was launched in September 2000.

TCIP differs to the other interventions described because rather than aiming at improving disaster response services, TCIP is a risk transfer strategy and assures repayment in case of damage. Thus, it can speed recovery. TCIP is an intervention which targets individual households by requiring them to make regular payments which afford security against potential catastrophic damage. Recent figures show that the number of policies totals 6.8 million, the number of claims is 21,545, and the penetration rate is quite low in Van at just 7.08% (38.9 per cent overall). At the household level, all of these state-level interventions seem to raise the prospect that risks can be better managed, and in fact all are cited as important measures for supporting resilience (Karanci et al 2014: 26-27).

It would also be important to consider how these changes can affect preparedness strategies. TCIP in particular is an intervention which seems to have a lot in common with preparedness measures; householders who take out and pay for it likely are aware of and concerned about hazard risks. It is a way of managing those risks a priori, rather than relying on emergency response and recovery operations. It is likely that uptake of TCIP (taking place between 1999 and 2011) would have had an effect on beliefs and cognition if, for example, it led to a reduction in the likelihood that householders develop high levels of hazard anxiety of the type that would affect 'normal' cognitive function; what we have earlier termed 'hazard denial'. In the ABM, this mechanism could be interesting because an insured agent would then be more readily able to form intentions to adopt disaster preparedness measures (it would mean that the Fear-t threshold is higher). In principle, it is arguable that those who have registered in TCIP are more likely to also carry out different preparedness measures, but we do not know if this is the case. It could also be the case that risk-shifting occurs; due to the presence of insurance, people are dismissive of preparedness actions entirely or partially (they may have a higher risk-intrusion threshold).

Therefore, as a 'what-if' experiment, consider the following 'intervention scenario' :

1. start the simulation and then after two years introduce the insurance intervention (e.g. at a rate of one agent per month up to 50% of agents).
2. Sub-scenarios are:

a) After adopting, insured agents have a higher risk tolerance level – meaning that risk is a less intrusive factor (based on a risk compensation logic).

b) After adopting, insured agents have a hazard anxiety threshold set at the maximum level - meaning that hazard denial does not occur

c) A combination of the two above sub-scenarios

Dissemination of information in a credible manner, by credible institutions was another state-level measure for supporting resilience. On the other hand, other observations focus on attitudinal changes among individuals and in society, risk and risk avoidance**.**

The second scenario that would be interesting to explore looks at the effect of introducing into the simulation a sub-population of experienced individuals. In this 'experienced agents' scenario, these individuals have a different rule-set using the following assumptions:

1) critical awareness is higher: for the sub-population of experienced agents the initial value is drawn from a different distribution than for other agents

2) critical awareness of experienced agents is not altered by messages

3) critical awareness of experienced agents does not decay

4) the threshold level for hazard anxiety of experienced agents is lower: for the sub-population it is drawn from a different distribution

5) hazard anxiety does not trigger experienced agents to form negative outcome expectations (leading to denial)

6) the threshold level for hazard anxiety triggers experienced agents to send messages to their peers based on their current state (awareness and anxiety)

Unlike critical awareness (which is fixed), hazard anxiety of experienced agents fluctuates. If it increases to the point where it reaches the threshold value, further producers' messages are ignored although the agent stays connected. At this point the agent starts to send messages to peers. The messages of experienced agents could increase awareness and concern (but should avoid triggering very high levels of anxiety) of peers. Hazard anxiety can decay in experienced agents.

The modelling task was also to explore the implications of different measures to increase resilience in the case studies with analysis of simulation experiments.

Scenario experiments, which compare different situations - often with respect to some baseline - can be used for exploratory analysis of intervention measures or intervention portfolios. We can apply this approach in disaster management research in communities to assess what are the influences of resilience-building measures and how they interact with human behaviour. This can generate new knowledge with the goal of supporting planning and policy processes in the future.

The 'intervention scenario' sketched above was implemented in the disaster preparedness ABM. Four simulations were run, comparing a no-intervention scenario with sub-scenarios a b and c. Since the intervention, TCIP insurance, is introduced over a precise time interval a different indicator was used for analysis. The response categories (L0, L1, L2 and L3) used earlier may not easily reflect changes over the short term, and therefore a simple count of number of individuals with intention to prepare was used as an indicator for which a time series output was generated.

The simulations were run in a similar way as previously, starting with two warm-up years, and then running for a further 4 ticks and then insuring one agent, repeating this last step 10 times, and taking measurements every 4 ticks. Parameters used were exactly as in the initial experiment (described in section 3.1.5). For each experiment, eight simulation runs were carried out. The results are shown in Figs. 3.1.11 – 3.1.14; each figure shows the time series lines for each run, as well as the mean value (shown in black).

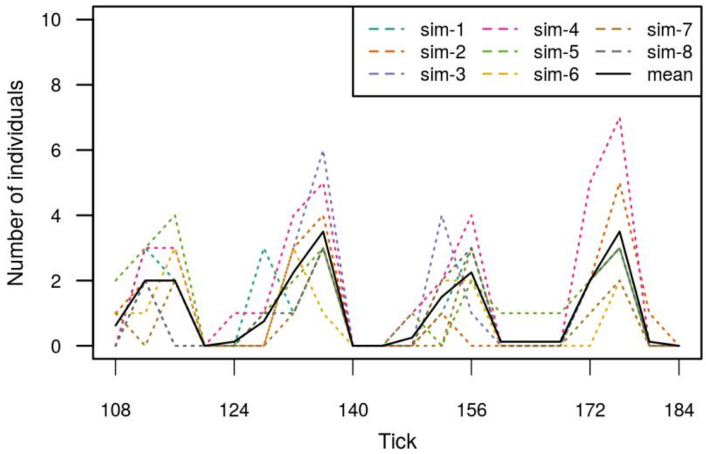

Figure 3.1.11: no-intervention scenario

The no-intervention scenario (Fig 3.1.11) shows a distinct periodicity with a cycle of around 20 ticks. This could be explained by two factors which may act together to drive the simulation: a) the timings of messaging which tend to raise the critical awareness and risk perception of individuals, and b) the decay parameter which specifies how the same variables fall back to below-threshold values. The average peak number of individuals is between 2 and 3 (out of 20).

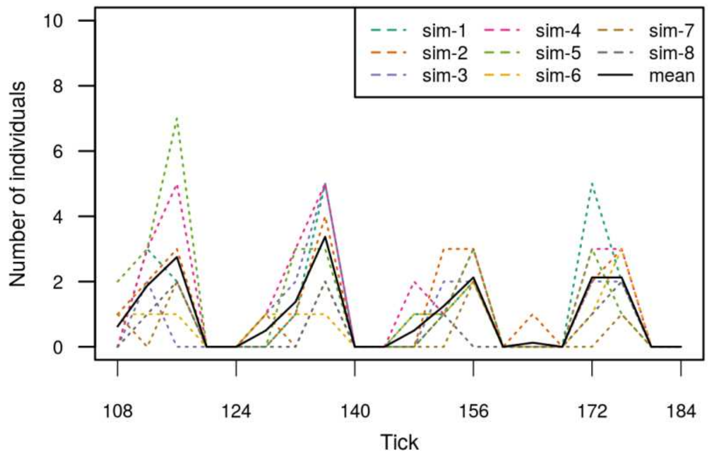

Figure 3.1.12: sub-scenario a)

The second simulation showing sub-scenario a) is quite similar showing that the specification of higher risk tolerance of insured agents, does not apparently affect outcomes very much. There is no noticeable difference between the preparedness intentions at onset of the intervention and during the later period after half of the individuals have adopted it.

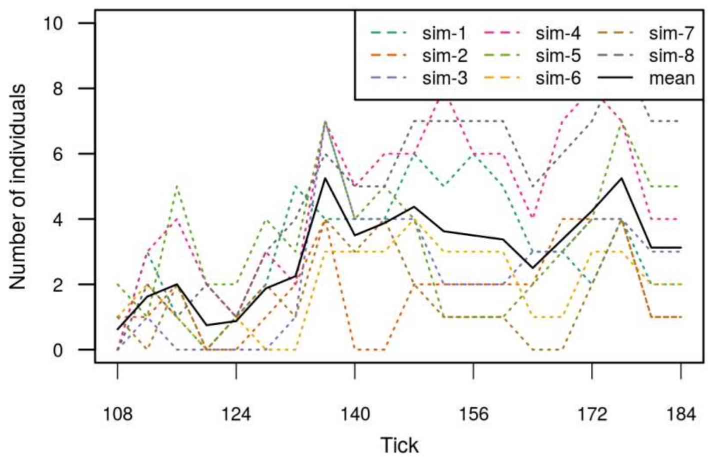

Figure 3.1.13: sub-scenario b)

The third simulation showing sub-scenario b) shows a change in relation to the no-intervention case. There is a steady increase from pre-intervention levels of preparedness intentions to higher post-intervention after around tick 150 where the mean number of individuals is around 4. Moreover, interestingly, the result seems to lose the periodicity that was present in the earlier simulations. Further investigation could investigate why this might be the case.

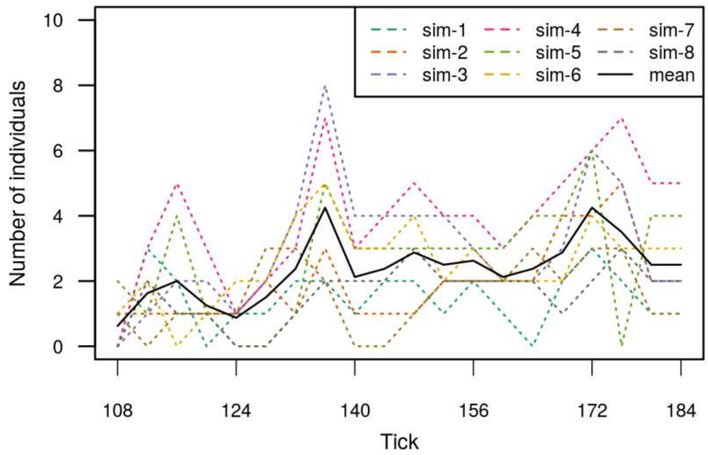

Figure 3.1.14: combining sub-scenarios a) and b)

The fourth simulation (which is a combination of sub-scenarios a) and b)) also is less periodic, although it seems to show that sub-scenario a) affects sub-scenario b), producing an interaction. The general trend is similar in terms of the direction of change (in the mean) over time, but the magnitude of change is smaller. In this case, the mean number of individuals, after tick 150, is around 3. In addition, the overall variance among simulation runs appears to be smaller.

The investigation of a TCIP-type intervention has demonstrated the value of ABM for generating further information of how behavioural responses may change – and how this can impact resilience over a certain time period of interest. It shows that different indicators are valuable for studying different research questions or exploring different management options. However, any new understandings generated remain dependent on a range of assumptions which need to be made transparent.

In this exploration to assess the impact of insurance on the population of agents, it was found that insurance could be particularly important in terms of its potential effect on hazard anxiety (sub-scenario b) whereas a risk compensation effect did not seem to be important (sub-scenario a). In other words, insurance could be important but only if acts towards preventing denial. However, this finding would need further study through other research, including simulation work to test other parametrisations, assumptions and other models.

3.2 Disaster response in Germany: performance of disaster management under change

3.2.1 Case study

When floods hit a community, disaster management and emergency services have to act as quickly as possible to safeguard people and property. However, effective flood management depends on several conditions, e.g. the availability of resources, the number of helpers that are deployable or the effectiveness of communication and coordination. Another crucial aspect is time: if lead times are too short or the time needed to put all necessary measures into place – the coping (i.e. *effective* response) time – is too long, disaster management might be unable to ensure the required protection. Disaster management has developed tried and tested routines over many years of service. However, under changing conditions, be it increased flood intensities, limited resources or changes in organisational structures, these routines might fall short. Worldwide disaster statistics show a strong increase in loss events, especially weather-related events such as floods, storms and droughts which have been occurring more frequently in the last decades (Hattermann 2014). Additionally, disaster events are not only occurring more frequently but often also with a higher intensity. Within just eleven years, for instance, the Free State of Saxony, Germany, has experiences three extreme flood events (2002, 2010 and 2013), of which two (2002, 2013) have exceeded the characteristics of a centenary flood and caused damages of several billion Euro. A large proportion of the flood prone area in this region is currently undergoing major demographic transitions with an ageing society, out-migration and low birth rates leading to significant population shrinkage BBSR, 2010). This shrinkage goes along with an economic decline, cutbacks in municipal finances and loss of urban functions, e.g. in the area of infrastructure. This also affects disaster management, as on the one side disaster management organisations (DMOs) are confronted with extreme events more often and need to provide higher protection, but on the other hand face doing this with fewer and fewer resources, not only in terms of money, technology or infrastructure, but especially in terms of manpower. Disaster management in Germany is largely based on volunteers, so a shrinking and simultaneously ageing population might also negatively affect the functioning of DMOs.

A third process of change is fairly recent: the fast development of the internet and mobile communication technologies has made information exchange very easy and fast. Moreover, the rise of social networks such as Facebook or Twitter has enabled civilians to exchange knowledge and organise relief efforts besides or in addition to official measures carried out by DMOs. This has been especially visible during the 2013 flood where a surge of voluntary helpers either followed the call for help or even self-organized to aid in the fight against the flood (DKKV 2015: 166). However, this response from civil volunteers did not have the same intensity in every region: bigger cities benefitted much more from the willingness to help, sometimes even experiencing an overload of volunteers, whereas small towns or rural regions depended much more on DMOs alone.

3.2.2 Idea behind the model

Analysing how one of these changes affects the functioning of DMOs might be possible with a pen and paper exercise. However, when change occurs in parallel in different dimensions – more frequent flooding, fewer available volunteers, and changing information and communications – their combined effects are not as easily predictable anymore. Our aim is to use a simulation model to analyse the performance of disaster management, identify how it is affected by change and try to determine shortcomings.

Several modelling studies exist that address natural hazards and their influence of community functioning, ranging from pre-disaster to post-disaster assessments. The complexity of these models ranges from more simple or conceptual models to very complex models that are often used for prediction purposes. Models like the Life Safety Model (Lumbroso and Tagg 2011) or MASSVAC (Hobeika and Jamei 1985) for example aim at predicting exact evacuation times for a specific disaster event or loss of life numbers. However, to achieve a good predictive power, these models also require accurate input data. Other models are more conceptual and address specific issues of disaster management like information sharing between emergency personnel (Zagorecki et al 2010). Several models focus on post-disaster recovery, e.g. (Nejat and Damnjanovic 2012) who investigate housing recovery with a specific focus on homeowners decision making or (Miles and Chang 2006; Miles and Chang 2011) who model recovery of critical services and community capital over a time period following a disaster.

The aim of the model developed in this case study is not to serve as a prediction tool but rather as a "what-if"-toolbox: you could compare it to a flight simulator that is used to evaluate the functioning of a plane both under normal and extreme conditions without putting the pilot or passengers at risk. Likewise, DMOs and other emergency services cannot exercise extreme events in real life, they can only plan for certain expectations (e.g. flood magnitude, resources needed) and develop action strategies in accordance with these expectations. When conditions change and these expectations fall short, the functioning of the organisations might not be guaranteed any more.

We use an agent-based modelling approach, because it allows us to incorporate, explicitly, the micro-level decision making of actors. Accordingly, this offers a capacity to observe these actors' joint emergent behaviour on a macro or system level (Holland 1992). Thus, we are able to model the behaviour of individual actors such as disaster management units that act independently to solve a common goal, i.e. protecting a community.

In this study, we want to analyse the effect of change on disaster management performance. We try to answer the following questions:

(1) Which dimension of change has the most profound influence on the performance?

(2) Can we identify thresholds for the capacities of disaster management to ensure protection?

(3) How do new developments like the involvement of civil volunteers influence the performance?

3.2.3 Description of the agent-based model

The description of the model loosely follows the (Overview, Design Concepts, Details and Decision) ODD+D protocol structure (Müller et al 2013).

3.2.3.1 Overview

Purpose The purpose of the model is to analyse the performance of disaster management and understand how it is affected by change (e.g. demographic, climatic, or institutional). The model is designed for both scientists and stakeholders, as an exploratory tool to understand the functioning of disaster management under change and as a discussion tool to illustrate these results to experts, address possible shortcomings and highlight options for improvement.

Entities, state variables, and scales. There are three main entities in the model: disaster management organisations (DMOs), disaster sites and sandbag reserves. DMO agents represent a group of members or distinct units of a disaster management organisation, which can work independently and autonomously to perform certain tasks that are assigned to them. They are characterized by different properties, e.g. group size and transportation capacity. Disaster sites and sandbag reserves are stationary entities with which DMO agents interact, e.g. via filling and distributing sandbags. Civil volunteers also represent a group of agents that can act independently from DMOs and can take over some tasks to support DMOs. However, they are restricted to simple tasks that don't require special training and they need information and coordination by disaster management organisations to become active. Space is explicitly included, the spatial setting of rivers, flood prone areas and the street network are based on GIS data. Time is modelled in discrete intervals with one unit (tick) representing one minute. There is no fixed time horizon, a model run stops after all tasks are finished. A conceptual diagram of the model is shown in Figure 3.2.1.

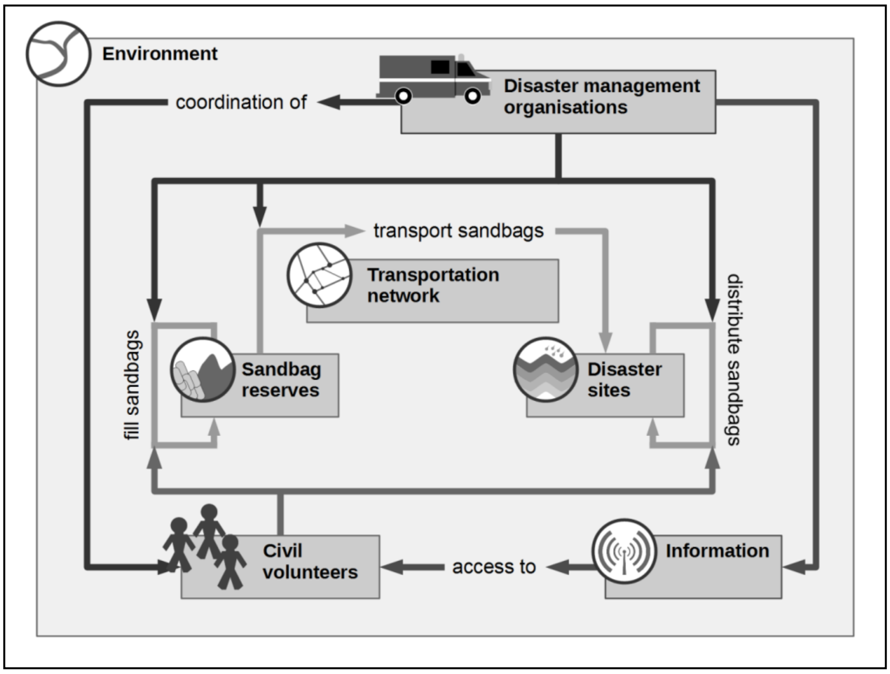

Figure 3.2.1: Model conceptual diagram showing entities and their relationships.

***Process overview and scheduling**:* At the beginning of each simulation, each DMO agent is assigned a task. In the current model version, it is either to fill sandbags or to transport and distribute sandbags. DMO agents will locate their nearest target site (either a disaster or a sandbag reserve), move there and perform the required tasks. Each DMO agent has a certain level of information access: *full information* indicates that they have complete knowledge about the state of all disaster sites at all times, i.e. how many sandbags are predicted to be needed at which site and when the tasks at a site are completed. The second level, *partial information*, implies that they can only acquire this knowledge through direct contact, i.e. when they are at a site, and remember it from then onwards. Agents can switch between tasks when necessary, e.g. when more helpers are needed for either filling or distributing sandbags. Civil volunteers follow a similar routine in that they can move to selected target sites and carry out tasks at these sites. The selection of sites depends on the information available to them. The simulation stops when the predicted required number of sandbags is present and distributed at all disaster sites. A flow chart of the general sequence of processes for DMO agents is displayed in Figure 3.2.2.

3.2.3.2 Design concepts

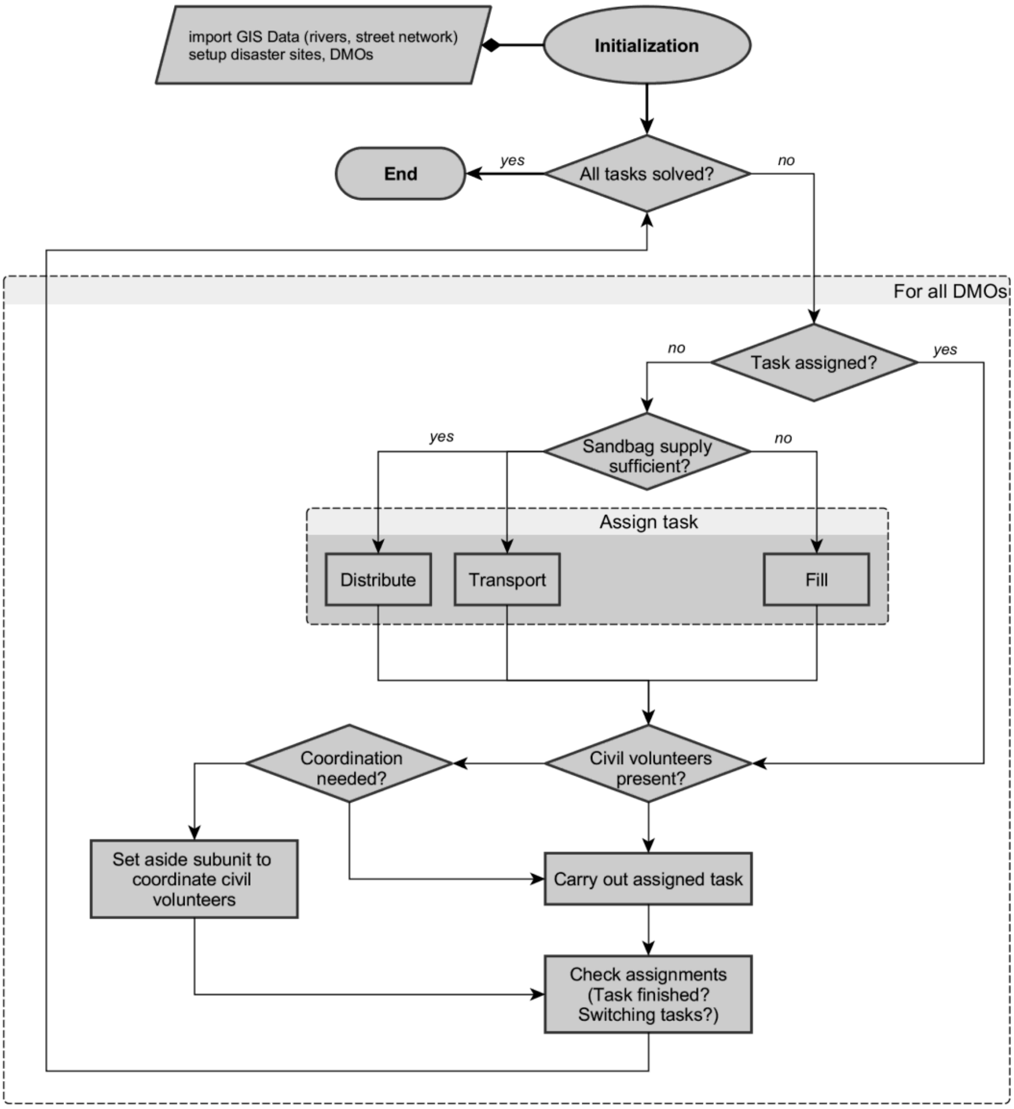

Figure 3.2.2: Model flow chart showing the general temporal sequence of processes.

Theoretical and Empirical Background: The model has been developed in order to depict the case of flood protection and disaster management in Saxony. ***Individual Decision Making*** DMO agents have to make decisions about which disaster site should be handled in which order, based on their level of information access, which can take on two levels: *full information* (agents know the current status of all disaster sites at all times), or *partial information* (organisations only perceive the status of the site when the visit it). ***Sensing*** DMO agents have full knowledge about the spatial settings of the model. This means they know the location of all target sites (disasters and sandbags reserves). ***Interaction*** Direct interaction between agents does not take place in the current model version. However, agents interact indirectly in several ways: they perceive where resources are needed and where not, e.g. they know if a disaster site is successfully protected. ***Heterogeneity*** Currently, within any single simulation all DMO agents are homogeneous in their properties. ***Stochasticity*** Disaster sites are randomly distributed at the beginning of each simulation. ***Observation*** For each simulation, the time needed to fulfil all tasks – the coping (or effective response) time – is measured.

3.2.3.3 Details

Implementation Details The model is implemented in NetLogo. A screenshot of the model interface with a sample simulation run is shown in Figure 3.2.3. ***Initialization and Input Data*** Currently, there are two case sites implemented in the model, the city of Leipzig and the Neisse region. For both areas spatial data for rivers, flood prone areas and the street network are imported from preprocessed GIS data layers. River and street network data are pulled from OpenStreetMap. Flood prone areas are extracted from LfuLG data. All data is initially simplified in ArcGIS to reduce complexity (e.g. reducing the number of nodes or approximating arcs with straight lines).

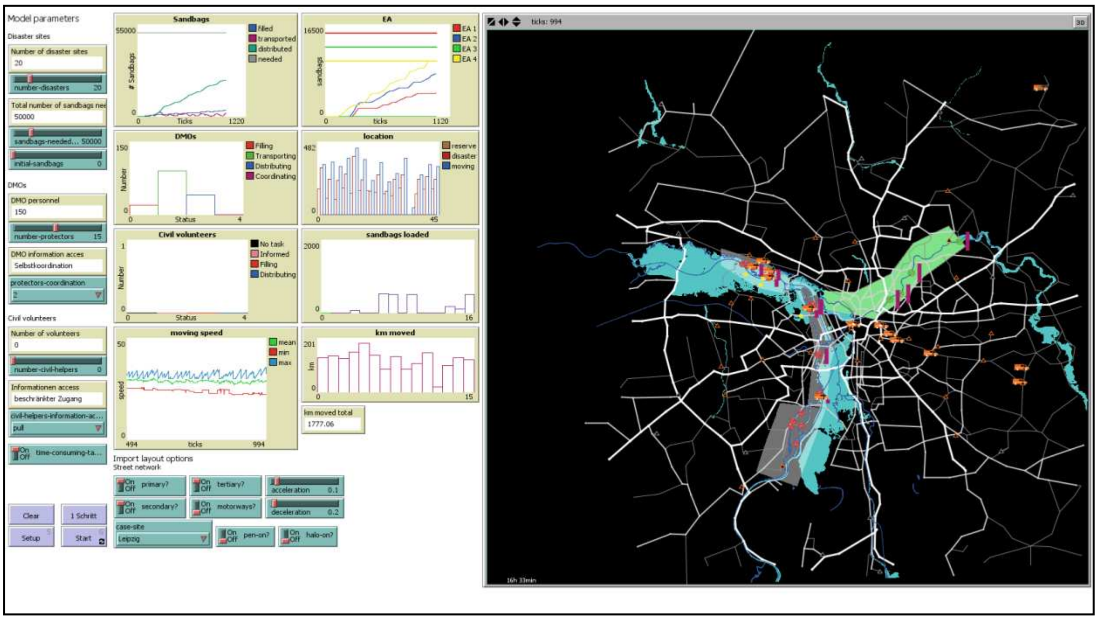

Figure 3.2.3. Screenshot of the NetLogo model interface. The map shows a snapshot of a running simulation, with DMOs moving along the street network and disaster sites in various states of protection. The green shaded area depicts a river section that is already protected whereas in the grey shaded areas sandbags are still needed at various sites.

3.2.4 Measuring performance – indicators for resilience

Maintaining the functioning of the community is directly related to the functioning and performance of the disaster management, i.e. the provision of protection against the negative impacts of a flood (or other hazardous events). To measure the performance of the disaster management and their capacity to cope with a single disaster event, we use the coping time t_{cope}. We define coping time as the time needed to put all necessary protection measures into place. Only if this time is below a certain threshold (in most cases the flood lead time), the community is safe. Over time, coping time can change, reflecting an increase or decrease in coping capacity, e.g. due to changes in DMO numbers or resource constraints. At the same time, the demand posed onto the organisations in terms of flood frequency and intensity can change too, possibly leading to a discrepancy between coping capacity and demand.

We can then analyse this discrepancy over time and determine how much change (i.e. of coping capacity) disaster management can endure and still have a coping capacity large enough to be able to provide the necessary protection under differing demands. In a graphical interpretation (Figure 3.2.4), this discrepancy is shown by the intersection of the black lines that represent the realization of protection measures over time, during a disaster event, and the red lines that represent the lead time threshold.

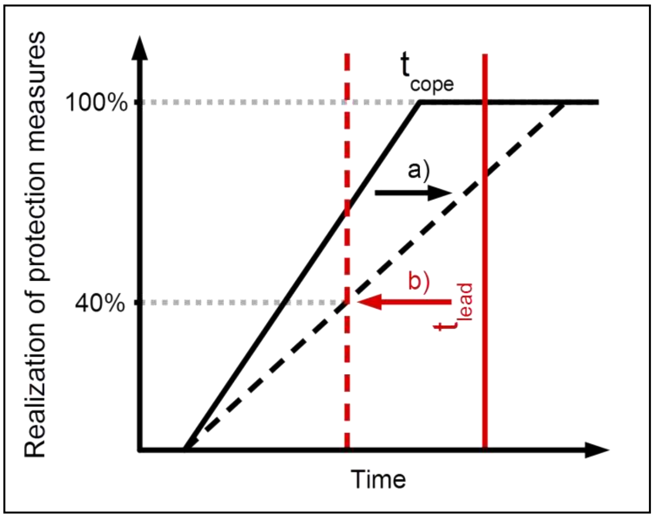

Figure 3.2.4: Measuring the performance of disaster management. Coping time tcope refers to the time needed to put all protection measures into place. When a) coping time increases or b) flood lead time decreases (due to shrinking resources or higher flood

A lower coping capacity leads to slower realization of protection measures. If this is then met with a shorter lead time, the community might be at risk if realized protection measures are below 100%. In our analysis we therefore measure the coping time in each simulation, where one simulation represents one concrete disaster event. In each scenario we then measure how the coping time changes with respect to the impact of change as a main indicator of how resilient disaster management is to change.

3.2.5 Scenario description

The analysed scenarios (Table 3.2.1) serve two purposes: a) to demonstrate the functionality and usefulness of the model and b) to illustrate the effects of a selection of change processes on the functioning of disaster management.

Process	**Impact**	**Affected model parameters**	**Range of variation**
Demographic change	Population decline	Number of DMOs	5 – 100
	Involvement of civil volunteers	Number of civil volunteers	0 – 200
Climate change	Shorter lead times	Coping time threshold	72h – 12h
	Increased flood intensity	Required total number of sandbags	50000 – 100000
		Number of disaster sites	5 – 80
Technological change	Improvements in transportation	Capacity of DMOs	250 – 2000
	Better information availability	DMO knowledge of disaster sites	partial information full information

Table 3.2.1. Scenario overview, showing change processes, their impact and affected model parameters.

Change mainly affects two components of the system: disaster management and its capacities, e.g. via the number of available helpers or resources; or the disaster event, e.g. flood intensities that result in changed demands. We also structure our scenario analysis along these two dimensions, so that at first we analyse how a given flood event can be handled under changing organisational settings. We then investigate the effects of changes in the flood and demand settings. The following table shows a list of the change processes, their impacts on the system level and the affected model parameters with their range of variation. As a third analysis, all scenarios were carried out for two different spatial settings: a) an *urban area*, the city of Leipzig in the north west of Saxony and b) a rural region, the Neisse between Zittau and Görlitz in the east of Saxony, adjacent the border with Poland. This comparison serves both as a test of robustness, to see if the model is applicable to different spatial settings, and whether change has different effects on the performance in different regions. For each parameter combination 100 simulations have been run.

3.2.6 The influence of the number of DMOs

For all conducted simulations, we measure the coping time as an indicator of how well disaster management can cope with a certain disaster event. At first, we take a closer look at the relationship between coping time, the number of DMO agents and their properties, while leaving the flood settings constant (Sections 3.2.6 and 3.2.7). Here, we can observe an exponential decline of coping time with increased number of organisations (see section 3.2.5). This general relationship holds across all parameter combinations and becomes especially evident on a double logarithmic scale: coping time (t_{cope}) and number of disaster management organisations (N_{DMO}) are apparently linked by a power law relationship, i.e.:

$$t_{cope} \propto N_{DMO}$$

The number of DMO agents is therefore a main determinant of the coping time. Decreasing DMO numbers (e.g. due to demographic change) lead to longer coping times. These coping times might exceed flood lead times, depending on the flood characteristics and geographical location of the community at risk. In Figure 3.2.5, we have superimposed three different lead time thresholds (72, 48 and 24 hours) to illustrate this relationship: To achieve a coping time below a 72 hour lead time threshold, at least 8 DMO units are needed in this setting. However, if this lead time threshold decreases to as low as 24 hours, then 45 DMO units are needed to stay under this threshold.

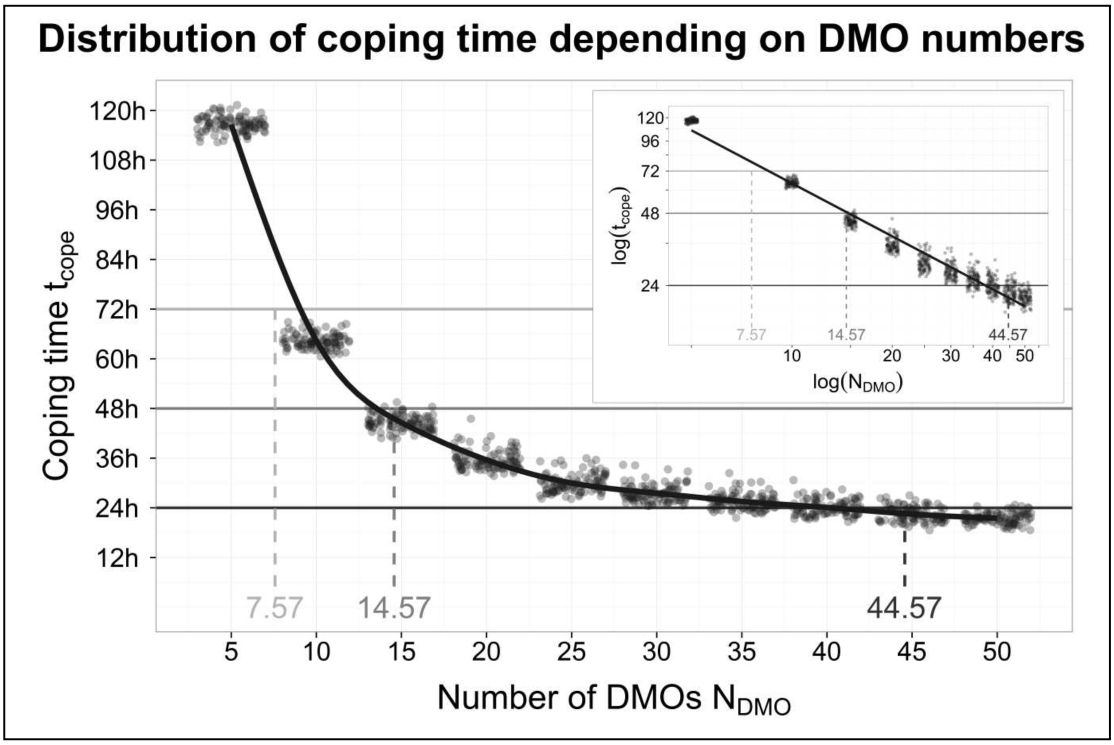

Figure 3.2.5. General qualitative relationship of coping time and number of DMOs. Coping time decreases exponentially with increasing number of DMOs, resulting in a Power Law relationship (as depicted in the smaller inset plot, showing the same data on a log-log scale). Results correspond to a flood setting of 40 disaster sites and a total demand of 50000 sandbags.

Based on these observations, we can reformulate this relationship as follows:

$$t_{cope} = \frac{1}{{N_{DMO}}^{(1-\varepsilon)}}$$

$$\log t_{crit} = y_1 - (1-\varepsilon)\log N_{DMO}$$

We can either calculate the critical coping time based on a given number of DMOs or, vice versa, calculate a minimum number of DMOs needed to achieve a certain coping time, e.g. a threshold number of DMOs that is needed to stay below the flood lead time. Results for this are presented under section 3.2.7.

3.2.7 Variation of DMO properties

The general relationship between the number of DMO agents and coping time remains unchanged when we change properties of the DMOs. However, quantitatively we can observe large differences in coping time when we vary a) the capacity and b) the information access of DMOs, as displayed in Figure 3.2.6. With a larger capacity (increased values on the x-axis), more sandbags can be transported in one round, i.e. one trip from sandbag reserve to disaster site and back, effectively reducing the number of rounds that are needed to achieve protection at one site. However, increasing the capacity also has its limits. The largest increases in performance (i.e. reduction of coping time) are achieved by doubling of the capacity from 250 to 500 sandbags, whereas the subsequent capacity increases to 1000 and 2000 sandbags only achieve a smaller reduction. This suggests that there is a marginal utility where the costs involved in improving the capacity of a single DMO is not worth the obtained performance increase. Increasing the number of DMO agents is more effective, and especially for high numbers of DMOs (e.g. $N_{DMO} = 80$), an increase in capacity results in almost no reduction in coping time.

The way that DMOs have access to information about disaster sites also influences coping times. With partial information access, DMOs observe the state of a disaster site only when the visit it, potentially leading to unnecessary trips to sites. With full information, DMOs know the state of all disaster sites at all times, so they avoid such unnecessary trips. The advantage of full information access is therefore especially evident when the number of disaster sites increases. Whereas in the case of only 10 disaster sites no substantial difference between both cases is observable, the reduction in coping time in the case of 80 disaster sites is quite large.

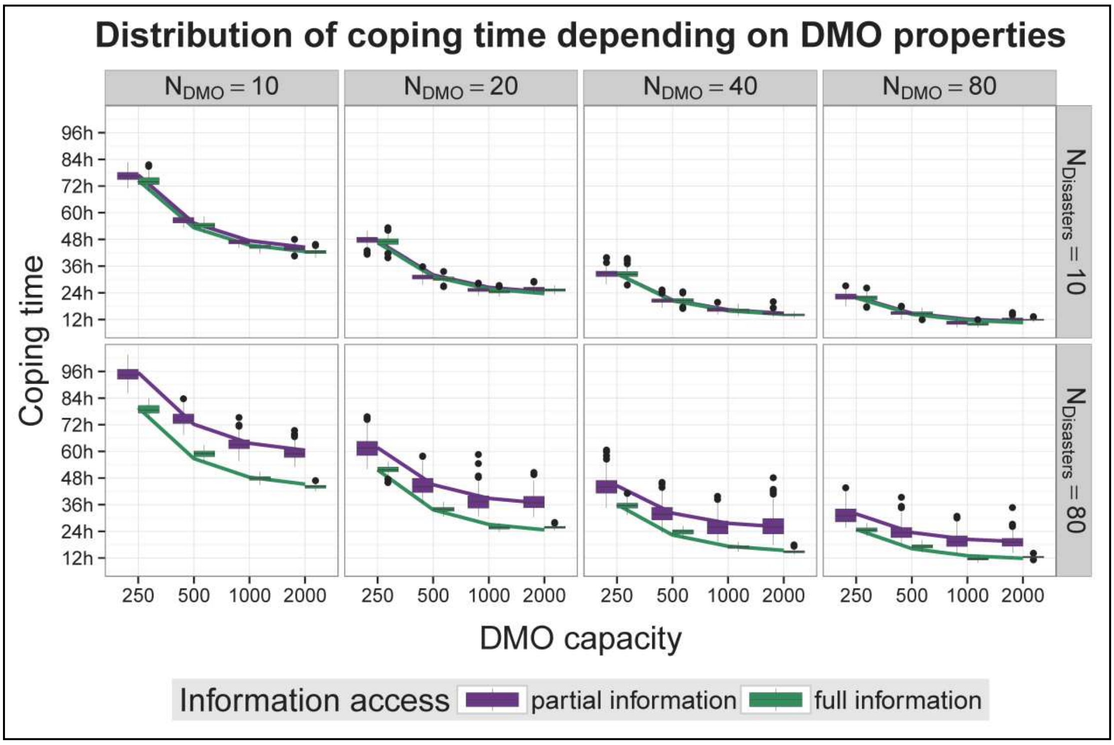

Figure 3.2.6. The distribution of coping time depending on i) the number of DMOs (panels from left to right), ii) their transportation capacity (x-axis) and iii) their information access (color-coded). Top and bottom panel row correspond to 10 and 80 disaster sites, respectively.

3.2.8 Variation of flood settings

Changed flood settings can be translated in either higher demands, in terms of resources or manpower, or shorter lead times. We have tested the performance of DMOs for different levels of demands in terms of a) the number of disaster sites and b) the total number of sandbags that need to be distributed. Variations in flood lead times have been considered in terms of the minimum number of DMOs needed to achieve a certain lead time. Results for this analysis are displayed in Figure 3.2.7. We see that in general the minimum number of DMOs increases when the lead time threshold increases. This is not surprising, as with increased lead times the same amount of tasks need to be solved in shorter time. However, this increase is non-linear: for high to medium lead times, the increase in DMOs needed is only subtle. For very short lead times, the numbers increase sharply. We can conclude that the number of disaster management organisations is particularly important in determining the performance of disaster management in areas with very short lead times, i.e. cities in the upper reaches of rivers.

The increase depends also a lot on a) the demand, here in terms of the number of disaster sites, as well as b) the capabilities of the DMOs, in terms of their transportation capacity and information access. When we compare the top and bottom panel of Figure 3.2.7a), we see that the curves show a much steeper increase when DMOs don't have full information access. Also, lower capacity and a higher number of disaster sites leads to an increase in the minimum number of DMOs needed. However, when we look at the bottom panel where organisations have full information access (i.e. they know the status of all disaster sites at all times), this increase is much more subtle. This shows that information access can play a large role to overcome either increased demands (shorter lead times) or shortcomings in resource supply (the number of DMOs = manpower).

3.2.9 Regional comparison

The two regions that we compared, a) an urban area and b) a rural region, are very different geographically, in their demographic situation, and in their infrastructure (see the transportation network maps in Fig 3.2.7, left and right panel). At first it

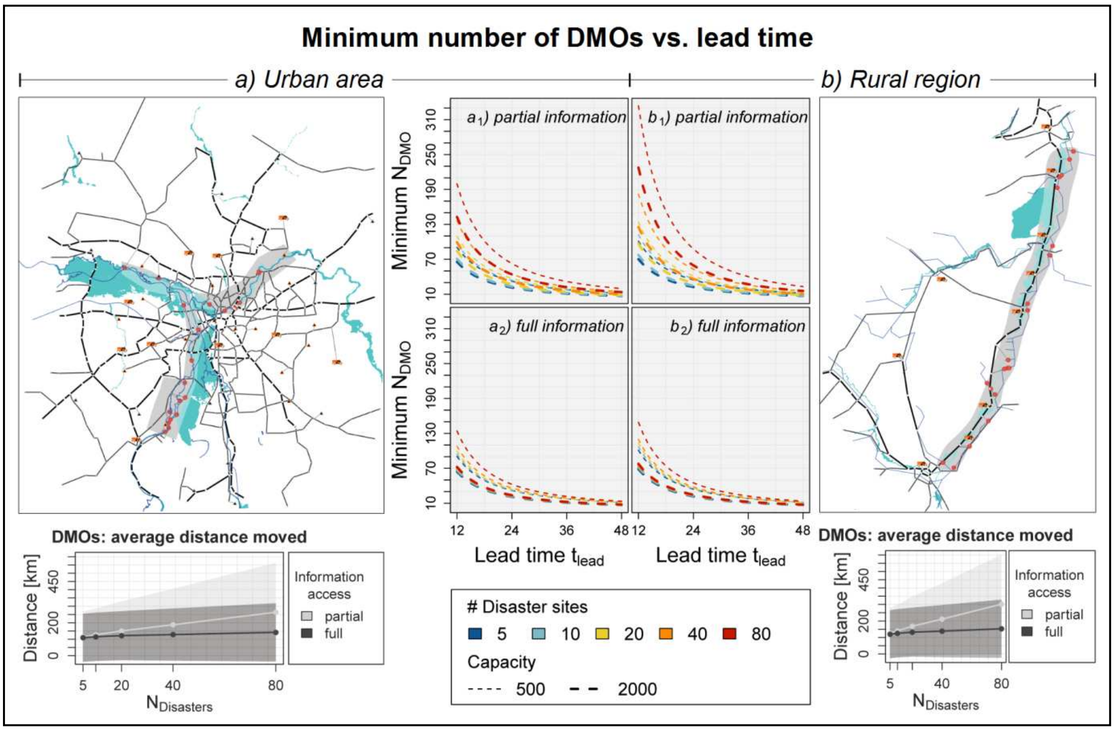

Figure 3.2.7: Minimum number of DMOs needed to achieve a specified lead time, compared across two different regions (a,b) and for partial (a_1, b_1) and full (a_2, b_2) information access. Number of DMOs are plotted in dependence of lead time for different numbers of disaster sites (5-80, color-coded) and DMO transportation capacity (line thickness). Maps on the left and right show the transportation network of the two regions, with comparison of moving distances below.

should be noted that the general qualitative behaviour of the model does not change across the regions, which confirms that the model performance is robust.

However, in the quantitative comparison of the results across these two regions, the spatial differences are not as apparent as we would have expected. The general pattern is very similar in both regions, with only subtle increases in minimum DMO numbers for the full information scenario when comparing rural and urban region. A more substantial increase can be seen in the rural region for the partial information scenario, and at very short lead times. Here, the limits in infrastructure seem to amplify the bottleneck of number of DMOs needed. Demographic change, leading to a reduction in the number of DMOs, therefore poses a stronger threat to rural, upstream regions as to urban, downstream regions.

3.2.10 The influence of civil volunteers

The results on this section are only preliminary as a range of analyses are either not finished yet or the simulation results still have to be analysed. In an initial test, we have compared the coping time for a fixed flood setting of 100,000 sandbags and 30 disaster sites and a fixed number of disaster management organisations, one time without civil volunteers and one time with 100 civil volunteers in addition.

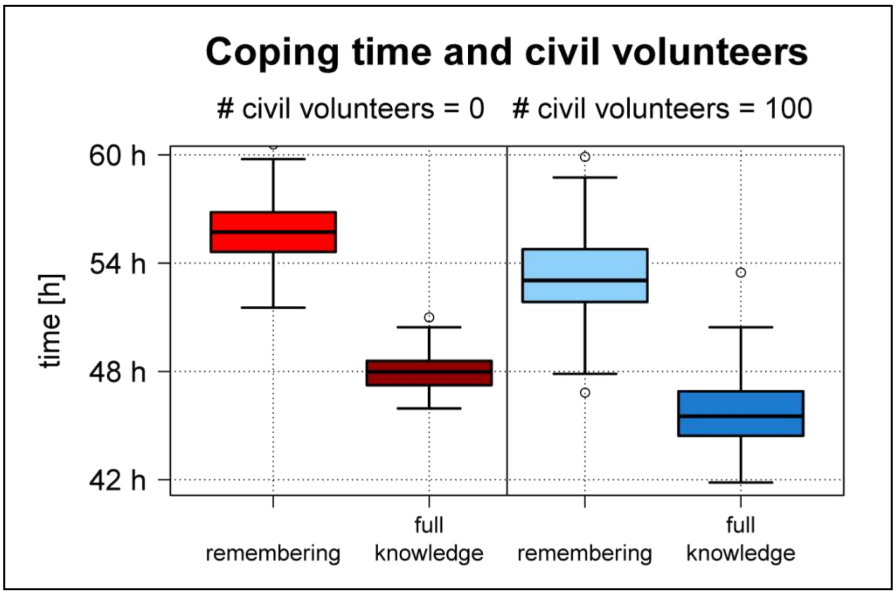

Figure 3.2.8: The influence of civil volunteers on coping time. The boxplot shows the distribution of coping time for a fixed number of 25 DMOs and total demand of 100000 sandbags. The two left panels show the coping time without civil volunteers, the right panels with 100 civil volunteers. Each case was tested with two settings for the information access of DMOs.

For both settings of information access of DMOs (i.e. remembering and full knowledge), additional civil volunteers lead to a reduction in coping time of about 2.5 hours. However, the reduction in coping time due to improved information access is in this case larger than the reduction achieved by adding civil volunteers: DMOs with full information access and no added civil volunteers still perform about 5 hours better than DMOs with restricted information access and added civil volunteers. This is of course a preliminary result and should therefore be treated with caution.

3.2.11 Conclusion

The model has shown that change has several effects on the performance of DMOs, but throughout all analyses the major driver that determines performance is demographic change through the number of disaster management organisations. If demographic change leads to shortages in available helpers and a loss in DMOs, the performance that is expected from disaster management may no longer be guaranteed. Even tried and tested routines might then fall short under such circumstances. The impact of demographic change varies in its strength between different geographic regions: urban – rural, as well as upstream – downstream. Especially in rural, upstream cities or communities, manpower is the ultimate limiting factor that determines disaster management performance, and deficiencies in this area can only partly be substituted with technological advances such as better information availability or increased transportation capacity. If we link these results back to our case study area of Saxony, a combination of short lead times and more rural areas can be found in the upstream area of the Mulde river. A more in-depth analysis of disaster management performance, its drivers and possible improvement options should therefore focus on this region.

Civil volunteers are a relevant group of actors that need to be incorporated into future planning for disaster management, but more detailed analyses are needed here to obtain a clearer picture.

4. Discussion and outlook

What we have seen in the above examples is that ABM is a useful addition to the toolkit for helping understand community resilience to disasters, and in particular that ABM adds a unique experimental and scenario capability to otherwise largely static or retrospective-looking methodologies.

4.1. Relationship of ABM with other cases and approaches

The extended discussion above on the linking between emBRACE Del. 5.3 (Karanci et al 2014) on the Turkish empirical data is also relevant to the discussion on emBRACE Del 4.1 (Karanci, Ikizer and Doğulu 2015). on Psychological Factors: further, the same could be extended to the emBRACE discussion on social learning (Matin et al 2015). We briefly discuss some of the ideas and lessons that could inform this work on social learning.

Learning about hazards can be challenging for homeowners, risk managers and the public. Many types of hazards, particularly severe ones, are extremely rare and in some circumstances entirely new to an area and to the population living there. Some experience shows that learning to cope with one hazard puts a community in a better position to cope with new hazards. Developing the capacity to learn from experience is of particular interest; this idea of 'learning how to learn' is ably captured in the concepts of double and triple loop learning.

This can also be seen as connecting the individual's understanding and willingness to learn, which are important for individual resilience, to institutional factors, which are important for capacity. According to this view, “Institutions and social networks can counter the conditions that limit learning, adaptability, and unintended consequences by increasing social memory and promoting communication and actions to improve adaptation and resilience” (Spies et al. 2014). Moreover, social learning incorporates the idea that non-experts are involved in adapting and sharing these actions.

The mechanisms of learning, including social learning, looped learning, adaptive learning, are a promising area of study for application of modelling. Work is also starting to apply ABM, building on earlier frameworks such as that of Conte and Paolucci (2001). The authors argue for a complex modelling approach which includes cognitive aspects that allow more adequate and complete accounts of different forms of social learning, e.g., social facilitation and imitation.

The authors pose the question: “If there is a way to obtain the same result with low-complexity mechanisms (such as routines and production rules), why then bother with high-complexity, cognitive mechanisms?” (Conte and Paolucci, 2001). They offer a set of arguments for why social learning is different from behavioural propagation and other phenomena. Similarly, Conte and Dignum (2001) conclude that “Essentially, all these results imply the capacity to compare others' behaviours to one's own internal criteria. None of them can be achieved if agents were enabled to simply adapt to one another's behaviours”.

Social learning here is defined (minimally) as: “the phenomenon by means of which a given agent (the learning agent) updates its own knowledge base (adding to, or removing from it a given information, or modifying an existing representation) by perceiving the positive or negative effects of any given event undergone or actively produced by another agent on a state of the world which the learning agent has as a goal.” (Conte and Paolucci 2001)

More recently, Bohensky (2014) studies 'learning dilemmas' in water management – understood to be gaps in learning capacity, understanding (perceiving) and willingness to learn. According to the author, ABMs are particularly well suited to investigating social and environmental conditions that potentially motivate or exhibit learning. Decision making takes place on the level of indicators (agents select one of three indicators) and strategies (agents change strategies depending on performance in relation to the current indicator), and changes follow either imitation or exploration of alternatives. Learning is said to occur when decision making results in success for the strategy/indicator evaluation. The results demonstrate the important principle that under changing conditions, agents in the model both have greater difficulty to learn – i.e. make successful decisions – and they are more likely to try alternatives, because changing (and paradoxically, learning) has greater incentives.

Greater consideration needs to be given to the role of social learning in communities, in disaster management organisations, between these actors and through learning across different levels. Research on social learning is at an early stage, particularly for building disaster resilience (Pelling et al 2015). ABMs can help to stimulate thinking about the mechanisms of learning, including the cognitive pathways and the social factors, in sufficient complexity to deepen our understanding of how people learn about hazards and how this process - of building resilience - could occur.

Linking ABMs to other methods within the context of disaster resilience is also discussed in Taylor et al. (2014): these other methods can include narratives, interviews, surveys & questionnaires, and structured-subjective methods such as Q-methodology (see Forrester et al 2015 for further details on Q-methodology). Furthermore, the potential for linking ABM with social network mapping (SNM) – and social network analysis (SNA) – are well developed within emBRACE's work package 4 (sic. both emBRACE Del 4.2 (Matin et al 2015) and this current deliverable). The next section deals with this in more detail and shows how these methods can be complementary.

4.2. Relationship of SNM with ABM

On face value, there are profound similarities between two methods. Using SNA, the social scientist is interested in whether the characteristics of an actor are correlated with its position in the network, and also if the measure of the network as a whole is correlated with some other indicator of the system, e.g. resilience. ABM is similarly modelling directly the actors (autonomous bits of software), endowing them with some initial data and rules. Simulations investigate the results of their interactions e.g. patterns/trends of risky behaviours. This is important because of growing recognition of the importance of cross-scale interactions in NRM. Both methods address the question of how localized interactions among social actors give rise to larger scale patterns or structures that may facilitate or constrain behaviour of actors.

Therefore both the social network / policy network analysis community and the ABM community have similar focus and a large overlap in interests. There are, however, important methodological differences. Main differences lie in at least three aspects. These relate to how the two methods respectively include (1) data (2) time and (3) complexity.

1) Data: Social network analysis, which studies interconnected socio-technical systems, is largely a data-driven method. Reviewing the literature of many applied studies (see Matin et al 2015), shows an attention to methodological detail in design of data collection and data preparation which is impressive. The major part of the research effort is put into the empirical study design and data collection and management. Agent-based models are, generally, less well-informed by empirical facts and data than would be desired. It is also the case that lack of data is one of the greatest barriers to the development of such models. Usually, data of different types are needed; usually, data are not available or are insufficient to inform some parts of the model. Therefore models are dependent on assumptions and guesswork; usually it is simply not possible to obtain enough data. As one result of this, models tend to lend themselves towards being used as exploratory tools and/or heuristic (communicative) devices rather than as metric tools.

Moreover, in some cases there is more of an emphasis on making models generalisable, or re-useable to address new questions; see Polhill et al. (2010) for an example. In this situation, where the same model is used for further research, there would be the possibility for adding new features as well as new data later on. For these reasons, relatively less time is spent on managing empirical data. In fact, in agent-based modelling, the major part of the research effort is put into analysis of simulation outputs i.e. managing simulation data.

Currently the rise in usage of online social media provides a wealth of information about social phenomena and human behaviour at scale. These data have been used extensively in social network analysis research to understand mechanisms behind social influence, spread of behaviour, etc, but their potential for inclusion in ABM has only started to be explored. See for further information Ciampaglia et al. (2014).

2) Time: A recognised challenge of SNA is that measurement of the final form of networks does not reflect the dynamics that have led to their eventual formation. In the absence of longitudinal network data agent-based modelling can be a complementary method for investigating the interplay of social processes, leading to the understanding of emerging network structure (see Cumming et al 2010).

Scenario analysis is an important approach for improving understanding of complex adaptive systems and for informing decision making in NRM. When the social network map has been constructed, it permits consideration of factors such as who are the connectors, where are the gaps, etc. and is a good basis for exploration of "what-if" scenarios. However, having information about possible future system states *where time is explicitly and precisely included* is an added value of ABM. This increases the quality of scenario analysis greatly because it becomes possible to explore how different management strategies may play out across different conditions.

3) Complexity: SNA models involve often relatively simple analyses to establish which are the most prominent actors and which are important to network connectivities on wider levels. These are aided by many accessible tools which can compute the numbers and produce visualisations. This simplicity has helped propel the method into wider recognition and use. However, one criticism is that this simplicity can also present a deceptive picture of social structures and their correspondence with outcomes. For example, Edmonds and Chattoe (2005) argue that simplistic network indicators are often not reliable, and that underlying mechanisms also need to be understood. In this respect, ABM seems to be uniquely capable of providing opportunities to analyse links between micro and macro features of a system, alongside its generating mechanisms.

4.3. Outlook

This section includes a set of think-pieces from emBRACE researchers working in the case studies that address the scope for future inclusion of simulation modelling in case study investigations, and it includes a list of ongoing challenges observed by the modelling teams that are also potentially common to all cases.

4.3.1 Northern England

Unlike the case studies in Germany, Turkey, and London, the Northern England case study has not used an agent-based modelling approach. However, modelling the role of flood management institutions, the development of civil society organisations and the response of communities to risk in the UK is a potential area for further research. We did discuss the ABM investigation of flood response patterns in Germany (section 3.2). We are also aware of other research (Dubbelboer 2015a; 2015b), which has looked at flood damage, risk and property buying decisions with ABM, concentrating on the recent (January 2014) extreme rainfall in the south of the UK. This model focused on addressing the shortcomings of the UK flood insurance system (i.e. insurance is not available or affordable for many homeowners). By including decision-making by private individuals (who may invest in property protection measures) and by local government (who may construct flood defences), the model was used to explore the implications of the proposed reinsurance system, FloodRe. It showed that the addition of such measures can, in the model, lower the flood risk, lower the damage payouts and over the longer term lower the FloodRe deficit.

Dubbelboer (2015a) suggests that further research is needed with ABM to identify the possible feedback loop between FloodRe insurance provision and economic incentives for flood protection.

Dubbeloer (2015a) is particularly interesting, because insurance (which is a mitigation measure that increases capacity to recover, i.e. it compensates for loss, it does not prevent it), was identified as an important factor in understanding community resilience for the emBRACE Northern England case study. (see the earlier section 3.1.7 in relation to TCIP). What is more challenging, perhaps, in comparing the north England case study with the Dubbelboer (2015a) ABM, is that the author monetised risk in the model and used it as an outcome indicator; yet includes little discussion of socio-cognitive aspects of how people may perceive risk in different ways (which was a clear finding in the qualitative emBRACE research). From the perspective of the Northern England emBRACE case study, what would be interesting would be to model the formation of support networks and show how these networks, CSOs and other community factors are an important mediator for how local residents can make their concerns and priorities more visible. This would build an improved understanding (see emBRACE Deliverables 4.2 (Matin et al 2015) and D5.6 (Deeming et al 2014)) of how communities in Cumbria are structured, and how they are sometimes able to pull in resources and to mobilise different forms of capital. This research could explore access to potential funding for mitigation measures (such as insurance and flood protection) and interaction with other council services such as social protection systems, which together contribute towards building community resilience.

4.3.2 South Tyrol

The emBRACE case study in South Tyrol focused on risk management, governance, and understanding coordination/communication among responsible authorities / civil protection and on risk perception of the population of the municipality of Badia. During the case study work we collected different kind of data (through questionnaires, interviews and participatory network mapping) that could serve as a base and be further investigated and integrated in the perspective of a ABM. Two particular areas stand out as potentially interesting for development of ABM. One area concerns further work on warning and evacuation and subsequent recovery operations in the region. The network mapping carried out within emBRACE focussed on alpine and therefore known hazards. The different maps, reflecting the experienced interactions of different organisations could be translated into a model to simulate different scenarios e.g. how the organisations interact in case of not known hazards. The case study work showed a well structured and resilient network based among other aspects on the trust and personal knowledge among members of the network. Out of this it could be interesting to investigate through a modelling approach possible scenarios where one or more of these members are not available.

One step in the data analysis of the population survey was to identify "type of respondents" according to their hazard experience and risk perception. The cluster analysis from the Badia study looked at risk awareness and experience, identifying 4 groupings of respondents based on different behavioural characteristics (Pedoth et al 2015: 38-40). These were: "Aware but not concerned", "aware and concerned", "not aware but concerned" and "Active, aware and concerned". A finding was that the experiential factors (including clean up) are linked with risk perception. Information about such groupings could be used to study heterogeneity by including sub-populations in an ABM (which would consequently have greater empirical validity). The case study collected also data on how people connect to organisations in case of an event. It could be further investigated what aspects are influencing the type of connections (age, hazard experience, degree of being affected) and create out of these characteristics different types of agents to be used for ABM. Such groupings could be used in a disaster preparedness model since both characteristics mentioned - awareness and concern - seem to be precursors of preparedness.

The second area centres on communication of risk, and improving the understanding of mechanisms that lead to safe or risky behaviour, particularly among visitors to the region. Tourists, who do not know the area, may have a lower perception of risk and/or may be ill-informed leading them to take reckless decisions compared to local people who have resided there for many years. It would be interesting to understand what factors help or hinder better communication of risk in this context. A modelling study could also look at trade-offs in the tourism sector; local government and business want to encourage tourism and help visitors get the most enjoyment, whilst addressing tourist concerns. On the other hand, safety procedures have to be in place along with strong risk communication, which may detract from visitor enjoyment.

Further work along these lines could build on the interest expressed by stakeholders in South Tyrol; one suggestion is to do modelling using participatory ABMs (P-ABM), as outlined in a recent paper (Taylor et al 2014) in which the authors discuss potential demands for modelling tools: "What urges decision-makers more – but is in many ways more difficult – is to consider how the short term future might unfold in terms of emerging risks and changing attitudes to risk, as well as management of preparedness/response systems. Research can also help with anticipation of further changes in the nature of community resilience. Modelling is one of the main ways of getting an insight into possible future states of the system, which can be usefully explored by carrying out scenario assessments. To do this is also crucial to elicit what stakeholders see as plausible future scenarios.”

4.3.3 London

Heat-waves, periods (2-3+ days) of unusually warm (dry or humid) conditions have profound impacts on human and natural systems. In cities these are exacerbated by the well documented urban heat island (higher temperatures in the city compared to the surrounding rural environment). Central London, where the temperatures may be 10°C greater than the surrounding rural countryside, is subject to heatwaves. These are expected to increase in frequency and intensity with projected climate change.

To study the impact and potential influence of human agents/actors on climate conditions in neighbourhoods across London, ABM is being undertaken in the framework of the model SUEWS (the Surface Urban Energy and Water balance Scheme, Järvi et al. 2011). A background to the case study is provided in Grimmond et al. (2014).

Of interest is how the actions of both individuals (property owners, residents, workers, etc.) and institutions (local boroughs, residents’ associations, Greater London Authority, national government, etc.) influence local climatic conditions and how these actions contribute to community resilience to heat waves.

SUEWS models urban radiation, energy and water exchanges for areas of about 250 m2 or larger (neighbourhoods), forced by meteorological data and information on underlying surface characteristics and human behaviour. Simulations across London have incorporated ABM to consider how individuals and institutions, through decisions of property characteristics (e.g. roofing materials, external cladding of building (material, colour), front gardens landscaped), to initiatives such as tree planting strategies or encouragement of BREAM or LEED2 ratings of buildings, are affecting (and can be used to affect) urban radiation, energy and water balances and thus climate conditions in neighbourhoods. Attention has focused on:

1. Anthropogenic heat fluxes – the additional heat emitted due to human activities (e.g. heating/cooling of building, transportation). Different levels of

activity, transport modes, transport speeds; home and commercial energy usage all impact this flux. This in turn, especially in areas with dense population or extensive commercial activity, results in a larger additional energy sources that exacerbate heat wave effects in a particular area.

2. Heating of the urban fabric, which is a key element in retaining heat in the urban environment sustaining higher temperatures particularly at night. Building materials and building densities are examples of individual and planning influences. These change both with new developments and with retro-fitting of areas.

3. The energy dissipated by evaporation (thereby not heating the air). A range of different changes in vegetation are considered: change of individual properties from front gardens to impervious surfaces, tree-planting strategies, green roof strategies, and the effect of different irrigation regimes (e.g. hose pipe bans).

Given the scale at which SUEWS is run (neighbourhoods not individual properties), individual decisions are not directly incorporated as singularities, rather emergent patterns for neighbourhoods are modelled. The modelling at Borough scale (Figure 1) allows the net spatial differences to be seen across Greater London to be seen for July 2012: for details see Grimmond et al. (2014). A number of challenges are evident based on the work done and the initial plan of work for the modelling tasks. First, it has been difficult to obtain data in suitable formats for modelling; data have usually been partial and not available in all formats, i.e. qualitative and quantitative data. It should also be called into question to what extent "complete studies of disaster risks are available". Data are generally fragmented and incomplete; this is also true in the case countries although related literature has compensated this to some extent.

4.3.4 IndicatorsWe have seen it as a challenge to decide on indicators and indicator systems, especially where there are potentially many candidate frameworks and measures, as in the emBRACE case studies. There is also a concern for the trust that we put in indicators. Indicators are potentially fallible since any such measure is only a proxy, and they also rely on assumptions which cannot easily be tested. One issue that has not been addressed is the reliability of measures that we are using or that others are using – measures for appraisal of resilience. Within the modelling case studies different indicators have been selected and tested – in some cases these are not the ones that conventionally are monitored.

Safety of measures is questioned, for example by Edmonds and Chattoe (2005), who, testing simple network measures, found that the kind of node and the position of node were important attributes affecting the outcome of interest ('satisfaction'). The authors concluded that simple 'network indicators' may not be reliable; however, use of more sophisticated network indicators' may be reliable – in particular circumstances.

In this study we have used a simulation approach where both the measures and the mechanisms (i.e. processes that we want to explain) can be investigated using model-generated data. These types of measures may - or may not - be safely used in different circumstances (timeframes, spatial scales, institutional and cultural differences in communities) to those for which they were originally developed. Therefore, caution must be exercised.

Having looked at the relationships between different approaches, it is clear that there are different strengths and weaknesses and that researcher communities for ABM, SNA and other approaches would greatly benefit by a larger degree of acquaintance with the methodological approaches of the other.

5. Conclusion

Agent based models can be good test beds for thinking about decision-making and management alternatives in many different human domains including those linked with transformative resilience to natural disasters. The modelling case examples presented in this report have demonstrated that a range of phenomena are readily amenable to study, from disaster preparedness measures to disaster response situations, whilst the review of history of simulation studies have shown that this work is still only beginning. Moreover, this literature review – and other empirical experience by the authors (cf. Forrester et al 2014) – has suggested that, whilst they can initially be difficult to understand, ABMs can also be very appealing to those that are engaged with resource management. Following this line of argument, and based on previous research, we can also suggest that ABM can be used with those experiencing the particular perturbation themselves if they are seen to have local relevance. For instance there are parallels with the use of P-GIS in disaster areas (e.g. see http://www.iapad.org/).

Models presented here have been used to test different 'intervention' scenarios which objectively seem feasible, yet the models themselves could not, yet, be considered reliable. The models have not been validated, and some of the results still seem difficult to explain. However, one lesson we can take is that when applying such "what if" scenarios, unexpected or counter-commonsense findings appear – the likelihood is that these novelties would then be extremely useful for planners to discuss.

Following Schlüter et al (2012) there are not only different uses for models (cf. Epstein 2008) but also different types of models to suit these different uses. Models that can be referred to as 'toy' models' or 'pilot' models can be specifically built for thinking about the issues, rather than producing a more fully developed, analysed, and verified model. Such models are structurally realistic enough (especially if they have been produced with participatory stakeholder input) to promote discussion, knowledge, exchange and learning, and exploration of various options. This holds true particularly if they are also backed by good facilitation processes.

Further, if such structurally realistic, participatory models can be parameterised, even roughly, one can start to make some linking to numeric models such as are routinely used by hydrologists, geologists, volcanologists, engineers and other technical experts who handle the technological side of disaster impact. This linking (ref In: Kemp-Benedict, Bharwani and Fischer 2010) will provide a critical correlation to include the social and the human in disaster modelling.

Further social data is needed for calibrating these pilot models to the circumstances of specific communities at risk. How best to implement management and planning interventions so as to create a more resilient system. This can aid hypothesis building about the mechanisms that produce patterns on the landscape and help find the appropriate set of strategies, regulations or interventions that give rise to desired outcomes.

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